How Do Company Announcements Affect the Frequency of Trading in Stocks? Essays on Market Microstructure and News Spillovers

Sylwia Nowak

A thesis submitted for the degree
of Doctor of Philosophy
at the Australian National University

September 2009

To Leszek

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university. The chapter titled *Macroeconomic Fundamentals, Price Discovery, and Volatility Dynamics in Emerging Markets* is the result of collaborative research with Jochen Andritzky, Andy Jobst, and Natalia Tamirisa of the International Monetary Fund (IMF), and was mostly written during my Ph.D. internship at the IMF's Research Department between January and April 2008. I am, however, the principal contributor to this chapter. To the best of my knowledge and belief, no other material has been previously published or written by another person, except where due reference is made in the text.

Some of the work in this thesis has been published or submitted for publication as journal papers or working papers. The material in chapter 2 has been published as

> Nowak, S. (2008). How Do Public Announcements Affect the Frequency of Trading in U.S. Airline Stocks? Centre for Applied Macroeconomic Analysis Working Paper Series 38/2008, Australian National University,

whereas the material in chapter 4 has been published as

> Nowak, S., Andritzky, J. R., Jobst, A., and Tamirisa, N. T. (2009). Macroeconomic Fundamentals, Price Discovery, and Volatility Dynamics in Emerging Markets. IMF Working Paper 09/147, International Monetary Fund.

The contributions of chapter 2 of this thesis were also presented at the Financial Integrity Research Network 2006 Doctoral Tutorial (December 2006, Sydney), the Econometric Society Australasian Meeting (July 2008, Wellington, New Zealand), the Brown-bag Seminar at Research School of Social Sciences at ANU (October 2008, Canberra), 21st Ph.D. Conference in Economics and Business (November 2008, Canberra) and the University of Melbourne (January 2009, Melbourne).

The material in chapter 4 has been submitted to *Journal of International Money and Finance* for possible publication, jointly with Jochen Andritzky, Andy Jobst, and Natalia Tamirisa. The contributions of this chapter were presented at the International Monetary Fund Research Seminar (April 2008, Washington DC, U.S.), Barclays Global Investors seminar (September 2008, Sydney), Time-Varying Correlation and Volatility Symposium (November

2008, Sydney), and the 21st Australasian Finance and Banking Conference (December 2008, Sydney).

Sylwia Nowak

Sylwia Nowak

September 1, 2009

Contents

List of Figures

List of Tables

Acknowledgements

First, I would like to express my sincerest appreciation and gratitude to Professor Heather Anderson, my committee chair, for giving me the opportunity to undertake this Ph.D. project, and for her invaluable advice and constant support throughout the period of this work. Her guidance, great insights on selecting interesting and challenging research topics, and occasional check-ups when I disappeared to the other side of the world were the key to the completion of this thesis.

Similarly, I would like to thank my other committee members, Dr Sirimon Treepongkaruna and Professor Farshid Vahid, for their support from the very beginning of my studies at the Australian National University (ANU), honest and timely feedback, and friendly reminders that research is (meant to be) fun.

Sincere thanks are also due to Jochen Andritzky, Andy Jobst, and Natalia Tamirisa of the International Monetary Fund (IMF), not only for a very productive and satisfying academic collaboration, but also for contributing to my wider macroeconomic education. Moreover, I am grateful to Geoffrey Bannister (IMF), Tim Bollerslev (Duke University), Robert Breunig (ANU), Stijn Claessens (IMF), Francis Diebold (University of Pennsylvania), Mardi Dungey (University of Tasmania), Steven Haider (Michigan State University), Raymond Liu (University of New South Wales), Ross Maller (ANU), Vance Martin (University of Melbourne), Brian McCaig (ANU), Daniel Smith (Simon Fraser University), and Tom Smith (ANU) for many valued comments and suggestions.

This research was supported by a generous scholarship provided by the Australian Research Council (Discovery Grant DP044995). The research conducted at the International Monetary Fund was funded within the Fund Internship Program, and supported by an internal grant from the IMF's Research Department.

I wish to thank the School of Economics for providing me with the intellectual space, support, and an excellent working environment to undertake this project. In particular, I would like to thank the Heads of the School of Economics, Professors Steve Dowrick (2006–2007) and Martin Richardson (2008–), for providing me with a fee-waiver scholarship and a much-appreciated Ph.D. allowance that enabled me to attend numerous academic conferences.

I owe a great debt to my family and friends who have encouraged and supported me throughout my time as a student. Special thanks are due to my officemate Jing Tian, the doctoral students at the School of Economics, and my "extended family" at Bruce Hall for their enjoyable company, stimulating technical and non-technical discussions, and their never-ending efforts to keep me sane. I am especially very grateful to Laura Crespo, Emma Phillips, and Rebecca White for helping me proofread something they hardly know. I also acknowledge the editing assistance provided by Jennifer McKibbin.

Finally, a big thank-you to Leszek for his unconditional love, support, and patience. This work is dedicated, as always, to him.

Abstract

The aim of this thesis is to investigate the properties of dynamic financial market processes and the impact of information events on the behaviour of market participants. This thesis comprises three essays.

The first essay examines how news releases, key microstructure features of market activities and crude oil futures returns affect trading frequency in U.S. airline stocks. Using the autoregressive conditional hazard (ACH) framework developed by Hamilton and Jordà (2002), we show that on average, trading intensity spikes prior and consequent to macroeconomic announcements, but decreases around firm-specific releases. We find that market microstructure variables have a small yet significant effect on trading frequency, with high trade volume and narrow bid/ask spread inducing higher trading intensity. Strong evidence is also provided to indicate that the intraday crude oil futures returns are relevant for modelling the probability of a trade in airline stocks within the next time period.

The second essay examines the forecasting properties of the ACH model in the context of predicting the conditional probability of a trade occurring within the next time interval. This study also develops three new, more flexible ACH specifications. We find that all ACH specifications strongly outperform benchmark forecasts. The most accurate forecasts are generated by the new ACH model that includes a measure of the length of time passed since the last observed trade (i.e. a no-trade duration). In contrast, the other ACH extensions based on more complex functional forms fit poorly, and are outperformed by the simple ACH model. Forecast encompassing tests clearly indicate the potential for further accuracy gains through forecast combinations based on the ACH model with no-trade durations.

The last essay is the result of collaboration with J. Andritzky, A. Jobst and N. Tamirisa. This study characterises volatility dynamics in emerging bond markets and examines how prices and volatility respond to news about

macroeconomic fundamentals. As in mature markets, macroeconomic surprises in emerging bond markets are found to affect both price discovery and volatility, with the effects on volatility being more pronounced and longer lasting than those on prices. The process of information absorption tends to be more drawn out in the emerging bond market than in the mature bond markets. Moreover, we observe systematic "news spillovers," with international news being at least as important as local news.

CHAPTER 1

Introduction

The aim of this thesis is to investigate the empirical properties of dynamic financial market processes and the impact of the news events on the intraday behaviour of market participants. This thesis presents three related essays that study the dynamic properties of the frequency of trading, price discovery, and price volatility. The analysis is conducted using high-frequency financial data (also called *ultra high-frequency data* by Engle, 2000) that in the limit contains records of every single transaction together with its characteristics (such as, for example, the price and the volume associated with a trade). Recent research has shown that empirical investigations of high-frequency data significantly advance a deeper understanding of market behaviour and information transition, see for example studies reported in special issues of *Journal of Empirical Finance* (Vol. 4, 1997), *Journal of Business and Economic Statistics* (Vol. 18, 2000), and *Empirical Economics* (Vol. 31, 2006).

It is well known that public announcements provoke strong reactions in financial markets. Asset prices and return volatility very quickly respond to news arrival, as traders discern the implications of newly acquired information for the fair value of the assets in their portfolios, in line with the theoretical model of Kim and Verrecchia (1991b). Within this framework, investors form their expectations about the true value of an asset before the release of public news and trade accordingly. Following an announcement traders revise their beliefs and trade only if there is a surprise component in the news, that is, the released data differ from their expectations. The recommencement of trading following an announcement is further reflected in an increase in trading activity, as investors rebalance their portfolios in light of new information to fit their risk preferences (Andersson, 2007). During the post-announcement period, transactions tend to occur more often (higher frequency of trading) and more shares/ bonds are traded in each transaction (increased trading volume).

Market microstructure literature posts that the increases in liquidity and volatility during the post-announcement period stem from information asymmetry between informed and liquidity traders (Kyle, 1985; and Admati and Pfleiderer, 1988), and investors' heterogeneity in interpreting public information (Kim and Verrecchia, 1997). In the Admati and Pfleiderer (1988) model, informed traders concentrate their trades during periods of high market activity, such as around public announcement times, to ensure that their informed trading has little effect on prices and that they can benefit from the liquidity externalities generated by other traders. This, in turn, promotes concentration of liquidity trades and generates even greater trade volume and more volatility. Kyle (1985) derives the same result—greater market liquidity following an announcement—arguing that the arrival of public news weakens the value of the informed trader's private information, thus making the market maker less concerned about adverse selection. Kim and Verrecchia (1997) argue that public announcements increase information asymmetry because investors have varying degrees of skill in interpreting news. This implies that the news impact on volatility dominates the effect on prices, with volatility remaining at elevated levels long after prices have adjusted.

This thesis investigates the impact of news events on the frequency of trading (chapter 2), price discovery, and price volatility (chapter 4). Trading frequency, as measured by the conditional probability of trade in a given time interval, plays an important role in assessing the dynamics of financial markets and market efficiency. Trading frequency determines *how quickly* prices, volatility and volume respond to an announcement and *how long* any response lasts. However, the impact of information arrival on the frequency of trading has been largely neglected in the literature. To the best of our knowledge, the first essay is the first empirical study to explain patterns in trading frequencies and to provide insights into the impact of public news releases, key microstructure features of market activities, and crude oil futures returns on trading frequency in U.S. airline stocks.

The analysis of trading frequency dynamics is conducted within the autoregressive conditional hazard (ACH) framework of Hamilton and Jordà (2002). Within this framework, the conditional probability of trade, called the *hazard rate*, is related to the past observed and expected trade durations. Trade durations—the irregularly spaced waiting times between two consecutive trades—often convey information about the news flow to market participants (see O'Hara, 1995, for an excellent review of the theoretical and empirical market microstructure models). The time series properties of trade durations are commonly analysed using the autoregressive conditional duration (ACD) model of Engle and Russell (1998), in which the expected waiting time until the next trade is intertemporally correlated with past durations. However, it is difficult to model the distribution of a duration when new information arrives within the analysed time interval (i.e. *between* the trades). Zhang et al. (2001) attempt to account for structural breaks in high-frequency data that correspond to information events by using a nonlinear threshold ACD model. A natural extension of the Zhang et al. (2001) work is to incorporate announcement variables into the ACD framework. However, it is often of more interest to know the likelihood of a trade in the next 5 or 15 seconds given the news release than to know how much time is expected to pass before the next trade occurs (Hamilton and Jordà, 2002). The ACH framework concentrates on the former issue whilst also utilising the ACD methodology of including past durations in the information set. As this approach facilitates the analysis of tick-by-tick financial data that is equally-spaced, it provides a convenient framework for analysing the impact of covariates that change between trades, calculating impulse response functions, and estimating multivariate models to study short-run spillovers between assets and between markets.

The key result reported in the first essay is that on average, trading intensity spikes prior and consequent to macroeconomic announcements, but decreases around firm-specific releases. Market microstructure variables have a small yet significant effect on trading frequency, with high trade volume and narrow bid/ask spread inducing higher trading intensity. Strong evidence is provided that raising crude oil futures prices significantly increases the probability of a trade in airline stocks within the next time period. Southwest Airlines, a domestic carrier renowned for their successful jet-fuel hedging program, is a notable exception.

The analysis of chapter 2 demonstrates, in line with the findings of Demiralp and Jordà (2001), Hamilton and Jordà (2002), and Andersen et al. (2007b), that the ACH framework allows for effective modelling of in-sample conditional probabilities. However, time-series models tend to be evaluated according to their out-of-sample forecast performance (Anderson and Vahid, 2001). Thus the focus of the second essay (in chapter 3) is on the forecasting properties of the ACH model in the context of predicting the conditional probability of a trade occurring within the next time interval. This is the first study in the ACH literature to examine the ability of the ACH model to predict out of sample.

The empirical forecasting evaluation of the ACH framework is conducted on time series of trades, computed from transaction and quote data of NYSE listed airline stocks. The financial tick-by-tick dataset entails a very large out-of-sample environment, so that the out-of-sample predictive accuracy of the ACH model can be statistically assessed. This essay also develops three additional, more flexible ACH specifications. These extensions address the modelling of the data dynamics and experiment with different functional forms of the ACH equation. The models are assessed and compared using out-of-sample probability forecast evaluation techniques such as quadratic and logarithmic probability scores, forecast encompassing tests, and probability forecasts combinations.

We find that all ACH specifications strongly outperform benchmark forecasts. The most accurate forecasts are generated by the new ACH model that includes a measure of how much time has passed since the last observed trade (i.e. a no-trade duration). In contrast, the other ACH extensions based on more complex functional forms fit poorly, and are outperformed by the basic model. Forecast encompassing tests clearly indicate the potential for further accuracy gains. We show that Kamstra-Kennedy forecast combinations (Kamstra and Kennedy, 1998) based on the ACH model with no-trade durations improve on the best individual forecast, in line with the literature for mean forecast combinations.

The impact of public news announcement on price discovery and volatility is the focus of the third essay (in chapter 4) which is the result of collaboration with Jochen Andritzky, Andy Jobst and Natalia Tamirisa of the International Monetary Fund. This essay is among the first to provide systematic evidence of the high-frequency volatility dynamics of emerging bond markets and the role of domestic and international macroeconomic fundamentals in the price discovery and trading activity process in these markets.

As in mature markets, macroeconomic surprises in emerging bond markets are found to affect both conditional returns and volatility, with the effects on volatility being more pronounced and longer lasting than those on prices. However, volatility remains elevated for about twice as long as in mature bond markets, possibly reflecting greater information asymmetries and lower liquidity in emerging markets. We observe systematic "news spillovers," with international news being at least as important as local news, and report strong asymmetric effects of good versus bad news. Finally, we show that although average intraday volatility has increased with the onset of the subprime crisis, the response to U.S. macroeconomic releases has become less pronounced, with domestic news in non oil-based economies gaining in importance.

This thesis proceeds as follows. Chapter 2 summarises the empirical literature that studies the impact of public announcements on market microstructure, asset returns and volatility. This chapter also discusses the most important features of the ACH model, the airlines dataset used in the analysis of chapters 2 and 3, and outlines the effects of new releases and crude oil futures returns on trading frequency. Chapter 3 investigates the forecasting properties of the ACH model. Chapter 4 uses a unique high-frequency dataset on emerging bond market prices and macroeconomic announcements to study the price and volatility dynamics in emerging markets, and the effects of domestic and international macroeconomic announcements. Chapter 5 concludes the thesis and offers some directions for future research.

CHAPTER 2

How Do Public Announcements Affect the Frequency of Trading in U.S. Airline Stocks?

2.1 Introduction

There is consistent evidence that public announcements affect intraday trading behaviour in financial markets. Numerous studies suggest a significant and instantaneous response of asset prices, return volatility and trading volume to macroeconomic and company news. However, the impact of information arrival on the frequency of trading has been largely neglected in the literature. The present study explains patterns in trading frequencies and provides insights into the mechanics of price discovery and the informational effectiveness of markets.

Exactly how information is impounded in prices is one of the "big questions" in the market microstructure and price discovery literature.[1] Several theoretical models describe the impact of news on the trading behaviour of different groups of investors. The informed speculation theories of Kyle (1985), Admati and Pfleiderer (1988) and Easley and O'Hara (1992) assume information asymmetry amongst (informed and liquidity) market participants and suggest that variation in market liquidity is partly due to scheduled public announcements. Other theories describe the effect of news events on the return volatility (see Nofsinger and Prucyk, 2003, for a review). These models imply that traders respond promptly to unexpected changes in microeconomic

[1] O'Hara (1995) is the classic reference for the economics of market microstructure. Recent surveys include Madhavan (2000), Stoll (2003) and Biais et al. (2005). The price discovery process is discussed in Hellwig (1980), Milgrom and Stokey (1982), Easley and O'Hara (1987) and Easley and O'Hara (1992).

and macroeconomic settings and that the rate at which transactions take place (i.e. trading frequency) plays an important role in determining the dynamics of financial markets and market efficiency. Trading frequency determines how quickly prices, volatility and volume respond to an announcement and how long any response lasts.

This study differs from others that look at microstructure effects on stocks by directly modeling the trading intensity and by estimating the probability of trade in the next time interval, using the Autoregressive Conditional Hazard (ACH) model of Hamilton and Jordà (2002). In the current paper the empirical investigation into the effects of macroeconomic and firm-specific news on trading frequency is conducted using high-frequency transaction and order data for three American airline equities traded on the New York Stock Exchange (NYSE). The airline industry provides a unique and exciting context for jointly modelling the frequency of trading, market informational efficiency and "trading spillovers," as discussed below. To the best of our knowledge, there are no empirical studies based on high-frequency airline equity data. Instead, most authors investigate intraday behaviour of either a single stock (IBM, see for example Engle and Russell, 1995 and 1998, or Rydberg and Shephard, 2003) or the constituents of the Dow Jones Industrial Average (Andersen et al., 2001, Hasbrouck and Seppi, 2001 and Hansen and Lunde, 2005).

An important contribution of this research is that it considers a very broad and varied announcements and information dataset. This dataset not only consists of a standard set of real-time United States (U.S.) government scheduled announcements; it also includes company news published by Dow Jones Business News and PR Newswire. This announcement set is further supplemented by the New York Mercantile Exchange (NYMEX) intraday crude oil futures price data. The significance of the present research design is twofold. Firstly, it allows for a unique study of how airline stocks, crude oil futures prices, and news arrival interact. Secondly, it facilitates an innovative investigation of the informational efficiency of crude oil futures prices that uniquely provide a single, readily quantifiable information source about the major component of U.S. passenger airline operating costs (ATA, 2006).

The remainder of the chapter is organized as follows: Section 2.2 briefly reviews papers that analyse the impact of public announcements on market microstructure, asset returns and volatility. Section 2.3 discusses the most important features of the ACH model and its usefulness in modelling the frequency of trade. Data and its statistical properties are described in Section 2.4. Section 2.5 presents model estimates and summarises the effects of new releases and crude oil futures returns on trading frequency. Section 2.6 offers conclusions.

2.2 How Do Public Announcements Affect Financial Markets?

A large volume of research has followed the pioneering event study of Fama et al. (1969) that assesses the efficiency of capital markets and how quickly they process the publicly available information. Interestingly, early papers considering the study of Fama et al. (1969), particularly the ones based on daily (or even less frequent) data, often report little or no evidence of a relationship between interest rates or equity prices and the arrival of public information. Dwyer and Hafer (1989) find that three-month Treasury bill returns and 30-year Treasury bond returns are unresponsive to the unexpected part of an economic announcement (defined as the difference between the initial announced values of the series and the median analysts' forecast). Hakkio and Pearce (1985), who use the average of bid and ask quotes for spot exchange rates taken at 09.00, 12.00 and 16.30,[2] demonstrate that exchange rate returns do not move in anticipation of economic announcements and that they do not react to economic news except for non-anticipated changes in the money stock. Damodaran (1989), in his study of a day-of-the-week pattern in the information content of dividend and earning announcements, finds that announcements explain only a small fraction of the weekend effect in stock returns. Similarly, Cutler et al. (1989), who analyse fifty of the largest one-day price moves in the Standard and Poor's Composite Stock Index since 1946, report that in most cases the information cited by the press as causing the market to move "is not particularly important." However, McQueen and Roley (1993) report that the relationship between percentage changes in stock prices and macroeconomic surprises is significant if one allows for different states of the business cycle. In particular, they show that news of higher-than-expected real economic activity, when the economy is booming, lowers equity prices, while the same surprises during recession result in higher stock prices.

[2] All times quoted in this study are New York times (i.e. U.S. Eastern Standard Time).

Once researchers start using high-frequency transaction data, macroeconomic news, including regularly scheduled macroeconomic announcements, is found to have a significant short-run impact on the intraday trading activities of financial markets. Much of the empirical literature looks at how announcements affect return volatility and examines the statistical significance of announcement variables. Other papers analyse the relationship between public information arrival and asset returns, trading volume and bid-ask spread.

In the bond market, Ederington and Lee (1993) report that public announcements are a major source of price volatility in Treasury bonds. Their study, based on five-minute futures returns, finds that price volatility is significantly higher between 08.30 and 08.35, when the major macroeconomic statistical releases such as the inflation indicators (CPI and PPI), employment reports and the Gross National Product (GNP) are made. Fleming and Remolona (1999), who use one-minute data from the secondary market for U.S. Treasury securities, document that the arrival of macroeconomic news induces a two-stage adjustment process for returns, spreads and trading volume. They report that prices react sharply to announcements for a brief spell of a few minutes, with the bid-ask spread widening and a considerable reduction in volume. In a second stage, which lasts up to an hour, high trading volume (four times higher than that during non-announcement days), high return volatility and moderately wider than usual spreads are observed. Consistent results are reported by Bollerslev et al. (2000) and Balduzzi et al. (2001).

In the foreign exchange market, in an important paper that analyses the effect of news on the intraday volatility, Bollerslev and Domowitz (1993) find that the news provides "a powerful positive and strongly statistically significant contribution to movements in the conditional variance." Interestingly, they use the lagged bid-ask spread as a proxy for the news inflow, arguing that "news events which change traders' desired inventory positions result in order imbalances, with the potential of changing spreads," and that "news can be thought of as simply changing the relative demand and supply for the currency, which might also affect the spread." However, they reject hypotheses that other market activity variables have independent effects on return volatility, in particular the intensity of quote arrivals.

In another FX study, Ederington and Lee (1995) use ten-second returns and tick-by-tick data to find that most of the price reaction to a scheduled macroeconomic announcement occurs within the first few minutes, with volatility remaining higher than normal for up to three minutes after the release. Working with slightly less frequent (five-minute) DEM/USD exchange rate returns, Almeida et al. (1998) demonstrate the same impact on returns within the first 15 minutes. Consistent with their findings, Andersen et al. (2003) show that conditional mean adjustments of exchange rates to news releases occur quickly, resulting in "jumps." However, they note that an announcement's impact depends on its timing relative to other related announcements.

Only a few empirical studies have highlighted the role of public information on the intraday price formation process in the equity markets. In general, stock prices and return volatility are also reported to respond to public announcements, but there are conflicting findings with regard to the speed at which the information is incorporated. For example, Adams et al. (2004) report that while CPI and PPI surprises have a significant negative impact on fifteen-minute investment returns, it takes up to 80 minutes for stock prices of large firms traded on the NYSE to adjust to the inflation news. However, their results are not robust, with one-hour returns being hardly affected by the announcements. This is in contrast to Jain (1988), who reports that CPI (but not PPI) and money-supply announcements are significantly correlated with one-hour investment returns.

A common aspect of most studies is that they only examine the impact of macroeconomic announcements, ignoring the role of firm-specific news. The few papers that do explore the role of company-related information in explaining price discovery concentrate on scheduled earning and dividend announcements, in isolation from other public releases. Moreover, there is no consensus on how fast stocks respond to such news. In one of the first studies that use intraday data, Patell and Wolfson (1984) report that stock prices respond to dividend and earnings news "within a few minutes, at most," but—in contrast to jumps observed in the FX market—the impact of news is "spread evenly over the first several post-announcement trades" (Greene and Watts, 1996). Even slower reactions to substantial shifts in dividend policy are documented by Gosnell et al. (1996). More recently, in a unique study that analyses the impact of unexpected negative company news events on the equity market (such as plane crashes or plant explosions), Brooks et al. (2003) report a relatively slow reaction of traders, with an initial price reaction of over twenty minutes.

This work complements the study of Brooks et al. (2003) and focuses on the impact of both scheduled and unscheduled macroeconomic and firm-specific announcements rather than just scheduled statistical releases. Furthermore, this study closely investigates the impact of news events on trading frequency, and as such contributes to the debate about equity market efficiency. The research is methodologically innovative, in that it uses the ACH framework, as discussed in the following section. This is in contrast to most empirical studies that use simple regression techniques—or, in the case of the effects of news on the return volatility—the generalized autoregressive conditional heteroscedastic (GARCH) framework of Engle (1982) and Bollerslev (1986).

2.3 Autoregressive Conditional Hazard Model

The autoregressive conditional hazard (ACH) model of Hamilton and Jordà (2002) is a statistical tool used for modelling the dynamics of discrete-valued dependent variables. The ACH model is based on hazard models, commonly used in statistics to analyse duration/survival data (for an excellent introduction see Lancaster, 1990). The *hazard rate* (or *hazard function*) is defined as a (limiting) conditional probability of an event occurring at time t (the next time period), given the information set Ω_{t-1} known at time $t-1$. In our case, we examine the probability of a trade occurring by the end of the next time interval, given a news announcement and other information events at time $t-1$. Previous studies have used the ACH model to model the probability of change of the level of the federal funds target rate by the Federal Reserve System (Hamilton and Jordà, 2002, and Demiralp and Jordà, 2001) and to study the occurrence of jumps in S&P 500 futures and U.S. Treasury bond futures returns (Andersen et al., 2007b).

It is a well-known fact that quotes and trades arrive at unevenly spaced time intervals, and the autoregressive conditional duration (ACD) framework of Engle and Russell (1998) is the standard way of modelling high-frequency and irregularly spaced financial transaction data. In the ACD framework, the waiting time until the next trade is intertemporally correlated with past waiting times (durations). However, it is difficult to model the distribution of a duration when new information arrives within the analysed time interval (i.e. *between* the trades). Zhang et al. (2001) attempt to account for structural breaks in high-frequency data that correspond to information events by using a nonlinear threshold ACD model. A natural extension of the Zhang et al. (2001) work is to incorporate announcement variables into the ACD framework. However, it is often of more interest to know the likelihood of a trade in the next 5 or 15 seconds given the news release, than to know how much time is expected to pass before the next trade occurs (Hamilton and Jordà, 2002). The ACH framework concentrates on the former issue whilst also utilising the ACD methodology of including past durations in the information set Ω_{t-1}. The ACD and ACH frameworks are explained in detail in Engle and Russell (1995, 1997 and 1998), Hamilton and Jordà (2002) and Demiralp and Jordà (2001). The most important features of the ACH model in the context of modelling high-frequency data are described below.

Consider a stochastic process that is a sequence of trade arrival times $\{t_1, t_2, \ldots, t_n\}$ with the nth trade arriving at the end of time t_n and $t_1 < t_2 < \cdots < t_n$. Also consider an associated *counting process* $N(t)$, which is the cumulative number of trades that have occurred by the end of time t (so $N(t) = N(t-1)$ if a trade does not occur in the interval $(t-1, t]$ and $N(t) = N(t-1) + 1$ if it does).

The length of time (the interval) between the $(n-1)$th and the nth trade arrival times is called a *duration* u_n, that is, $u_n = t_n - t_{n-1}$. The ACD(p, q) model predicts that the conditional expectation of the duration u_n is a weighted average of p past durations and q past expectations, that are known at time t_{n-1}. That is, given past observations $u_{n-1}, u_{n-2}, \ldots$, the ACD(p, q) model implies that

$$\mathbb{E}[u_n | u_{n-1}, u_{n-2}, \ldots] \equiv \psi_n = \omega + \sum_{j=1}^{p} \alpha_j u_{n-j} + \sum_{j=1}^{q} \beta_j \psi_{n-j}. \tag{2.1}$$

Using the definition of the counting process, Hamilton and Jordà (2002) rewrite equation (2.1) as

$$\psi_{N(t)} = \omega + \sum_{j=1}^{p} \alpha_j u_{N(t)-j} + \sum_{j=1}^{q} \beta_j \psi_{N(t)-j}, \tag{2.2}$$

where the expectation $\psi_{N(t)}$ is formulated at time t_{n-1}. The expected conditional duration written as (2.2) is a *step function* that only changes if the trade occurs during time interval $(t-1, t]$, i.e. only when $N(t) \neq N(t-1)$. In this setting the *hazard rate* h_t is defined as

$$h_t \equiv \Pr\left(x_t = 1 \mid \Omega_{t-1}\right) = \Pr\left(N(t) \neq N(t-1) \mid \Omega_{t-1}\right), \tag{2.3}$$

where $x_t = 1$ if a trade occurs within $(t-1, t]$ and $x_t = 0$ otherwise.[3]

As with the GARCH and ACD models, equation (2.2) can be easily generalised to account for linear effects of covariates $\mathbf{z}_{t-1}$ known at time $t-1$, such as public news releases, crude oil prices and market microstructure variables. However, the exogenous covariates can change even if a trade does not occurs. Indeed, the key feature of the ACH model is its ability to study effects of announcements that occur *between* trades. This implies that the expected conditional duration ψ_t changes by the end of every (calendar) time interval, through

$$\psi_t = \psi_{N(t)} + \delta \mathbf{z}_{t-1}. \tag{2.4}$$

where δ denotes a vector of parameters.

The relationship between the hazard rate and the conditional duration can be derived using properties of the geometric distribution. The expected length of time until the next trade is

$$\psi_t = \sum_{j=1}^{\infty} j\,(1-h_t)^{j-1}\,h_t = \frac{1}{h_t}, \tag{2.5}$$

or

$$h_t = \frac{1}{\psi_t}. \tag{2.6}$$

The reciprocal relationship between the expected conditional duration and the hazard rate makes sense intuitively: if the expected length of time until the next trade is, for example, four minutes, then the probability of a trade within the next minute is 0.25. Correspondingly, if the expected conditional duration is two minutes, than the probability of a trade occurring within the next minute is 0.5. Of course, changing the units in which time is measured affects the magnitude of the expected conditional duration and the corresponding hazard rate. For instance, if the expected conditional duration is $\psi = 2$ minutes or 120 seconds, then the probability of a trade within the next time period is 0.5, if time is measured in minutes, or 1/120,

[3] We follow Hamilton and Jordà's (2002) definition of the hazard rate. However, in the duration literature a definition of an instantaneous rate of event occurrence per infinitesimally unit of time is often used. That is,

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr\left(x_{t+\Delta t} = 1|\Omega_t\right)}{\Delta t}.$$

Scaling by Δt implies that the hazard rate can be any positive number. This is in contrast to the hazard rate implied by equation (2.3), which is bounded between 0 and 1.

if time is measured in seconds. This highlights the need for avoiding lengthy time intervals, as the probability of a trade occurring within every such period is, uninterestingly, almost always equal to one.

Feasible estimation of the parameters of interest requires some model modification, though, as at the time of the $(n-1)$th trade (when the expectation about ψ_t is formulated) the value of $N(t)$ is unknown, as are the values of $u_{N(t)-j}$ or $\psi_{N(t)-j}$. To overcome this problem, Hamilton and Jordà (2002) specify the hazard rate as the reciprocal of the expected conditional duration lagged one period. However, this approach does not utilize all the data available at time $t-1$, which prompts us to modify the model as following

$$h_t = \frac{1}{\psi_t}, \tag{2.7}$$

$$\psi_t = \omega + \sum_{j=0}^{p-1} \alpha_{(j+1)} u_{N(t-1)-j} + \sum_{j=1}^{q} \beta_j \psi_{t-j} + \delta \mathbf{z}_{t-1}. \tag{2.8}$$

Then the parameters in (2.8) can then be estimated using maximum likelihood techniques, with the conditional log-likelihood specified as

$$\mathcal{L}(\theta) = \sum_{t=1}^{T} \left\{ x_t \log(h_t) + (1-x_t) \log(1-h_t) \right\}, \tag{2.9}$$

where $\theta = (\omega, \alpha', \beta', \delta')'$ denotes a vector of parameters.

2.4 Data Sources and Properties

2.4.1 Airlines Intraday Data

Our empirical analysis focuses on the transactions and order data for three airline companies listed on the New York Stock Exchange, observed during August and September 2006.

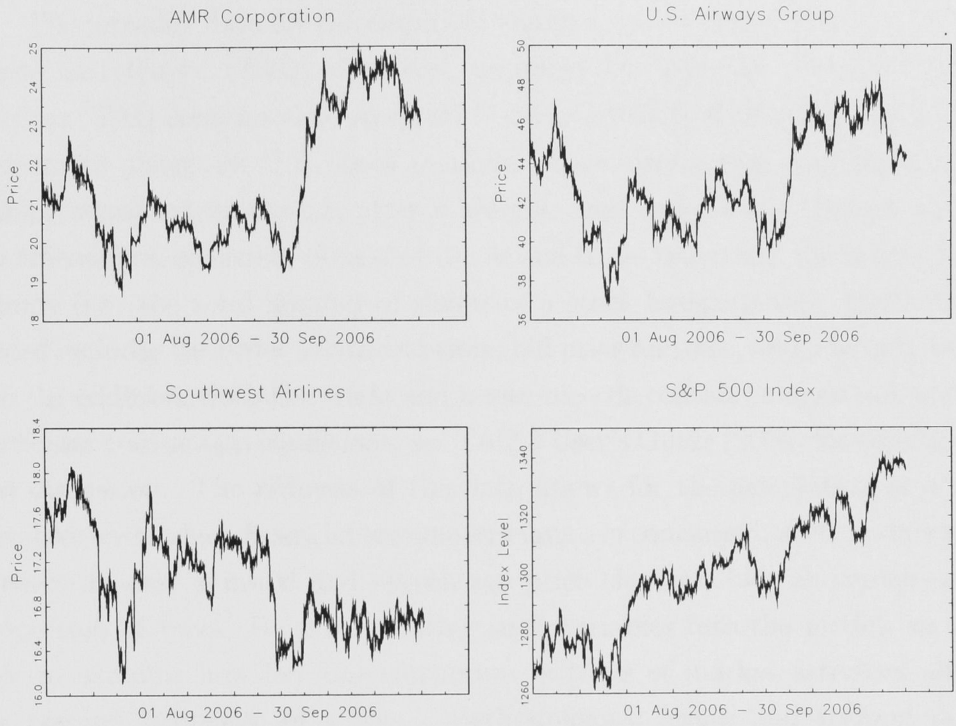
Air transport is one of the world's largest industries, with a history of strong underlying growth in traffic volumes and revenues. The direct value of U.S. commercial air transport was estimated to be more than USD 100 billion in 2000, or USD 163 billion including aircraft, aircraft parts and airport expenditures (DRI-WEFA, Inc., 2002). Despite this, the behaviour of air travel is highly cyclical, with growth falling dramatically when the economy is in a recession. After exhibiting strong growth during the late 1990s, the industry experienced an unexpected downturn in air travel resulting from the terrorist attacks in the U.S. on 11 September 2001, the Severe Acute Respiratory Syndrome (SARS) epidemic in 2003 and the Iraq war (ongoing since 2003). The huge financial losses incurred by airlines since 2001 (USD 32.3 billion dollars between 2001 and 2004, ATA, 2006) have presented enormous challenges to the industry, and forced many airlines to embark on programmes of severe cost-cutting and fleet rationalisation, with some large U.S. carriers filing for bankruptcy (United Airlines and U.S. Airways).

A strong recovery in traffic volumes during 2004 coincided with the year of strongest global economic growth for three decades (UN-DESA, 2005). In 2005, the scheduled world airline industry generated revenues of nearly USD 413 billion (IATA, 2005). During 2003–2006, total operating revenues of U.S. airlines increased on average by 12.12 percent per annum (ATA, 2006), with a rise in the real passenger air transportation output of 21.93 percent in 2005 (BEA, 2006). However, the increase in total operating revenues did not translate into a profit recovery primarily due to the huge increase in fuel costs (world oil prices in June 2005 reached USD 60 a barrel).

Our study is based on all stock transactions for shares in the top three U.S. airlines listed on the NYSE[4] over the period of August and September 2006 (see Smallen, 2006, for a ranking of U.S. airlines). These airlines are AMR Corporation (AMR), Southwest Airlines Co. (LUV) and U.S. Airways Group Inc. (LCC). During the sample period, crude oil prices reached a long-time peak of nearly USD 77 a barrel in early August 2006, and then fell more than USD 12 in mid-September (NYMEX, 2006). The Dow Jones Industrial Average rose to 11,669.39 on 26 September, the second-highest close of all time (Patterson, 2006). The airline industry became "one of the hottest sectors," quickly recovering from the effects of the terrorist plot in London on 10 August and increased security measures. On average, major U.S. airline stock prices went up 15.3 percent between 20 August and 20 September, outperforming analyst rankings by 70–80 percent (Wenning, 2006). Receiving much media coverage, airline stocks were traded almost continuously, becoming a perfect candidate for an empirical intraday study. Figure 2.1 illustrates the price

[4]Traditionally, stocks of larger and more frequently traded firms are listed on the NYSE, rather than on Nasdaq or AMEX. This study focuses on large firms—and hence on the NYSE—to avoid thin-trading and insider-trading problems (see Easley et al., 1996, for discussion on how the probability of trading based on private information depends on trading volumes).

Figure 2.1: Price Behaviour of Airline Stocks and the Standard and Poor's 500 Index



Notes: The figure graphs the price behaviour of airline stocks and the Standard and Poor's 500 Index, sampled at five-minute intervals from NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ and CQG databases.

behaviour of the selected stocks and the Standard and Poor's 500 Index over the sample period.

The selected airlines jointly carried 268.1 million passengers on their flights in 2005, 35.95 percent of the industry total (Smallen, 2006). In particular, airlines belonging to AMR Corporation, American Airlines and American Eagle Airlines, carried 115.6 million passengers on their international and domestic flights during 2005, more than any other airline. American Airlines ranks amongst the largest scheduled passenger airlines and the largest scheduled air freight carriers in the world (Smith Barney, 2006). During 2005 it provided scheduled jet service to approximately 150 destinations around the world (NYSE, 2006). American Eagle Airlines, a regional carrier, was the fastest growing of the top ten airlines, carrying 17.9 percent more passengers in 2005 than in 2004. The second largest airline, in both the size and growth rankings, was Southwest Airlines. Southwest is a domestic low-fare airline that provides frequent flights to 61 airports in 31 states throughout the United States (NYSE, 2006). LUV carried 88.4 million passengers in 2005 and experienced an annual growth of nine percent. Finally, the third largest airline corporation was U.S.

Airways Group, the owner of U.S. Airways and America West Airlines, which jointly carried 64 million passengers on their flights in 2005.

The intraday data for the empirical analysis was obtained from the NYSE Trade and Quote (TAQ) database, supplied by Wharton Research Data Services. TAQ contains time-stamped historical details of all individual trades and orders placed on U.S. stock markets. Each transaction contains a time stamp, measured in seconds after midnight, that reflects the time at which the transaction occurred, details of the actual trade price, and the transaction volume (i.e. the total number of shares of a stock bought/sold). Each quote record includes the order's date and time, bid price and size, and offer price and size. In addition, both the trade and quote records contain information about particular transaction conditions, see TAQ 3 User's Guide (2006) for definitions and discussion. The richness of the data allows for the calculation of other variables with which financial econometricians are concerned, such as duration between trades, nominal and percentage price changes, bid-ask spreads and proportion of buys. By incorporating such variables into the model, we are able to examine how key microstructure features of market activities affect the trading frequency of stocks. Methodological issues and stylized facts about continuous–time datasets are discussed in Goodhart and O'Hara (1997), Guillaume et al. (1997) and Hautsch (2004). Theoretical studies that analyse market microstructure are outlined in O'Hara (1995), and these include Kyle (1985), Admati and Pfleiderer (1988) and Easley and O'Hara (1992).

To get the data into a form suitable for analysis, we must first make several adjustments to eliminate erroneous quotes and trades. Firstly, we remove trades and orders posted on exchanges other than the NYSE. The NYSE quotes have been shown to determine (or, if not, to match) the national best quote most of the time (Blume and Goldstein, 1997) and since all trades on any exchange must be executed at the national best quote, Engle and Patton (2004) argue that other exchanges are simply not relevant.

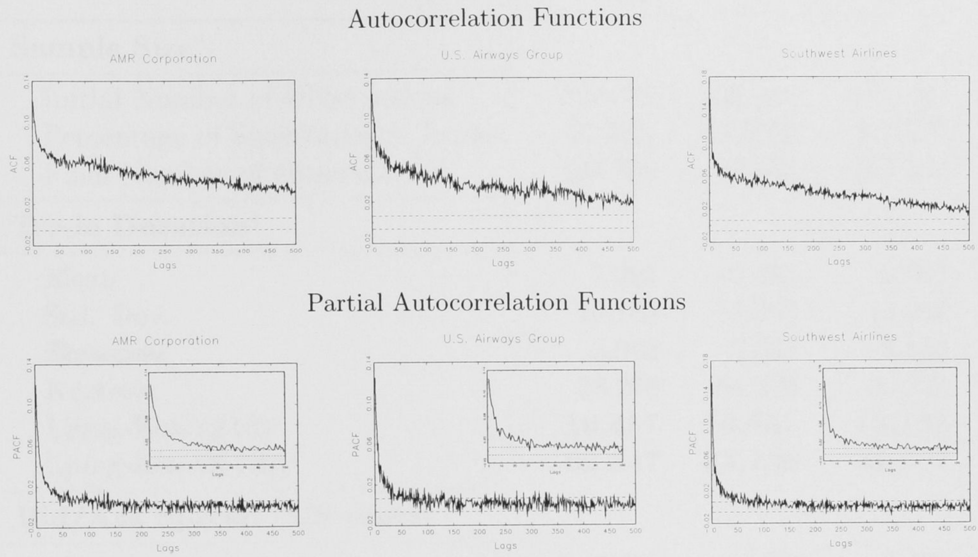
Next we remove trades that are out of time sequence or cancelled (TAQ's CORR field other than zero or one) or have a non-standard sales condition such as delivery of the stock at some later date (TAQ's COND field not blank nor E). We also eliminate quotes that do not arrive under normal trading conditions but we keep those that arrive during news arrival times (TAQ's MODE field must be equal to 1, 2, 3, 4, 6, 10, 11, 12, 19, 20, 27, or 28). Further, we exclude trades and quotes with non-positive prices, or observations for which the bid/ask/trade price is greater (less) than 150% (50%) of the previous bid/ask/trade price (Boehmer et al., 2005). Finally, we eliminate quotes with spreads larger than USD 4.00 or less than USD 0.00 (Huang and Stoll, 1994).

Once the data has been cleaned, we then match trades and quotes using the "two seconds rule" proposed by Lee and Ready (1991) and recently updated by Vergote (2005). According to this algorithm, trades are matched with quotes that are time-stamped at least two seconds before the trade. Then transactions outside NYSE regular trading hours and in the first 15 minutes of each trading days are removed. Finally, we merge trades that have exactly the same timestamp by constructing volume-weighted average prices and summing up the total volume of the trades. Simultaneous trades arise due to split-transactions (large orders on one side of the market automatically matched against several smaller orders on the other side of the market, Hautsch, 2004) and retail traders' tendency to execute orders at the round prices (Veredas et al., 2002). The occurrence of split-transactions justifies eliminating zero trade durations (see for example Engle and Russell, 1998, and Engle and Patton, 2004), though aggregation of the simultaneous trades mutes the information effects (Gunn, 2007).[5]

Table 2.1 presents the number of observations before and after the aggregation of simultaneous trades, and the summary statistics of the aggregated data. All stocks are traded very frequently, with trade durations averaging between 7 and 11 seconds. An average transaction has a volume of 519 to 1,144 shares and a bid-ask spread of 1 to 4 cents. We observe overdispersion in the distributions of trade durations, spreads and volumes (as the standard deviation exceeds the mean) and strong positive skewness, which indicates a declining proportion of long durations/large spreads/big volumes. All variables exhibit significant autocorrelation, as formally tested using Ljung-Box statistics. This is further documented in Figure 2.2, that shows the autocorrelation (ACF) and partial autocorrelation functions (PACF) of trade durations. We observe positive, highly significant and very persistent dynamic dependencies, that are characteristic for long memory processes. Further, both trade frequency and durations reveal very strong diurnality

[5]An alternative approach, taken by Ulph (1999), Meitz and Terasvirta (2006), and Gunn (2007), is based on the assumption that trades arrive equally across the second in which they are recorded. Dividing the number of trades across this second creates a dataset that contains many very short durations and no null durations. The main drawback of this procedure is that it markedly complicates the estimation and yields very unusual ACD coefficients (Gunn, 2007).

Figure 2.2: Sample Autocorrelation and Partial Autocorrelation Functions of Trade Durations



Notes: The main graphs illustrate the ACF and PACF for the first 500 lags of trade durations, and the inserts illustrate the PACF for the first 100 lags of trade durations. The dashed lines represent 95% confidence bounds. The sample consists of NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ database.

(see Figure 2.3). The probability of trade exhibits a U-shaped pattern over the course of the day, that is also characteristic for volatility, trade volumes and bid/ask spreads. On average, trades are about twice as likely to occur during the opening auction and immediately prior to the market's close than during lunch-time. Conversely, the time-of-day seasonality in trade durations exhibits an inverse U-shape, as first documented by Engle and Russell (1998).

2.4.2 Crude Oil Futures Prices

In his seminal paper, Hamilton (1983) points out that all but one of the U.S. recessions between the end of World War II and 1973 were preceded by a sharp rise in the price of oil. Further, he finds a strong negative relationship between oil price changes and GNP growth. Subsequent empirical studies of Burbidge and Harrison (1984), Gisser and Goodwin (1986), Rotemberg and Woodford (1996), Mork (1989) and Raymond and Rich (1997), to name a few, confirm that there is a statistically significant negative correlation between oil prices and aggregated measures of economic activity. While this relationship is sometimes reported to be much weaker when the sample period is extended to the 1990s (Hooker, 1996), new research attributes this to

Table 2.1: Descriptive Statistics of Trade and Quote Data

	AMR	LCC	LUV
Sample Size[a]			
Initial Number of Observations	158,392	108,102	123,747
Percentage of Simultaneous Trades	16.22%	14.56%	19.07%
Final Number of Observations	132,705	92,362	100,154
Trade Duration[b]			
Mean	7.291	10.473	9.662
Std. Dev.	10.153	17.893	13.096
Skewness	3.942	5.685	3.593
Kurtosis	28.278	64.308	26.223
Ljung-Box Q(15)[c]	**16,457**	**10,551**	**13,132**
Ljung-Box Q(100)[c]	**62,847**	**33,108**	**41,767**
Bid/Ask Spread (US cents)			
Mean	1.668	3.496	1.192
Std. Dev.	1.257	3.037	0.573
Skewness	4.798	3.600	8.319
Kurtosis	44.396	54.957	221.417
Ljung-Box Q(15)[c]	**67,187**	**47,864**	**30,628**
Ljung-Box Q(100)[c]	**114,008**	**86,920**	**40,694**
Trading Volume[d]			
Mean	1,143.912	518.845	1,023.068
Std. Dev.	3,373.932	1,149.03	2,787.942
Skewness	38.730	17.480	50.908
Kurtosis	3,265.082	559.014	7,006.073
Ljung-Box Q(15)[c]	**2,601**	**3,025**	**1,434**
Ljung-Box Q(100)[c]	**5,830**	**9,258**	**3,377**
Proportion of Buys	55.24%	55.28%	54.11%
Market Value[e]	4.497	3.833	13.788

Notes: The table reports sample sizes and summary statistics for trade and quote data for AMR Corporation (AMR), U.S. Airways Group (LCC) and Southwest Airlines (LUV). *Sample period*: NYSE trades and quotes that occurred between 9.45 and 16.00 for August and September 2006. *Data source*: TAQ database.

[a] Number of trades before and after the aggregation of simultaneous trades.

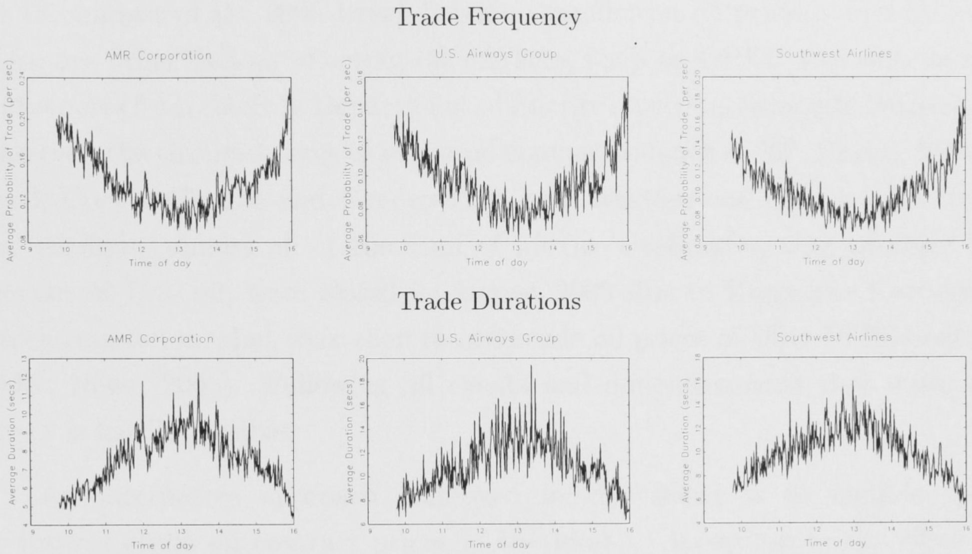
[b] Aggregated trade durations, measured in seconds.

[c] The Ljung-Box Q(15) and Q(100) statistics test the null hypothesis of no autocorrelation of orders 15 and 100 and follow $\chi^2(15)$ and $\chi^2(100)$ distributions under H_0, respectively. Statistics provided in **bold** are significant at 5% level.

[d] Number of shares traded.

[e] Stock market-capitalisation of 1 August 2006, calculated by multiplying the number of shares outstanding by the closing price (in billions of USD). *Source*: CRSP database.

Figure 2.3: Average Intraday Pattern of Trade Frequency and Trade Durations



Notes: The time between trades is measured in seconds and the time of the day is measured in hours since midnight. The averages are based on five-minute intervals of trading activity. The sample consists of NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ database.

misspecification of the functional form. In particular, Hamilton (1996, 2003) and Balke et al. (1998) demonstrate that the relationship between crude oil prices and macroeconomic indicators is nonlinear.

Regardless of the functional form, all financial markets anticipate shocks to oil prices and respond to them quickly.[6] This is not surprising, as oil—"the lifeblood of America's economy" (U.S. Department of Energy, 2006)—supplies more than 40 percent of U.S. total energy demands. This suggests that it will be useful to incorporate oil shocks into models of trading frequency in stock markets. The incorporation of shocks to the oil market is particularly relevant for modelling the frequency of trading in airline stocks, given that refined crude oil is used to produce a wide array of petroleum products, including diesel and jet fuels.

Unfortunately, the study of oil shocks is not an easy task, as oil prices are affected by a wide range of factors, and an oil shock cannot be strictly defined (Hamilton, 2003). One should observe the current political situation and military developments in OPEC countries (with the Iranian uranium

[6]References to oil prices in Western news reports are usually either references to the spot price of either West Texas Intermediate (WTI, also known as Texas Sweet Light) as traded on NYMEX or the price of Brent as traded on the Intercontinental Exchange (ICE). WTI is the benchmark in oil pricing and is the underlying commodity of the NYMEX oil futures contracts (EIA, 2006).

enrichment program being the most discussed news during the summer of 2006), and in the Middle East in general (see Twin, 2006 and Evans, 2006 for the impact of the 2006 Israel–Lebanon conflict on oil prices). In addition, there are other factors affecting oil markets, such as OPEC announcements and reports from the U.S. Department of Energy regarding Strategic Petroleum Reserves, the circumstances of major oil companies (such as BP, Exxon, Mobil, Shell, ChevronTexaco and Conoco Phillips). Weather can matter a lot, too. For example, almost all of the Gulf of Mexico's refineries, that produce 25 percent of U.S. oil, were closed in August 2005 due to Hurricane Katrina—which resulted in what were then record crude oil prices of USD 70.85 a barrel (ABC News, 2005). Following all events and announcements that move oil prices is hardly feasible.

An alternative approach employed in this study is to include spot or futures crude oil contract prices in the model. According to the efficient market hypothesis, these prices unbiasedly incorporate all information available to market participants. We choose to include the NYMEX light sweet crude oil futures contract, as worldwide it is the most liquid and actively traded financial instrument on a physical commodity (NYMEX, 2006). As such, the use of tick-by-tick crude oil futures prices data in the model not only serves as a proxy for a (potentially) incomplete set of oil related surprises, but it also incorporates a continuous information measure. It also allows for an innovative investigation of trading spillovers in the context of stock and crude oil futures markets. Current front-month light sweet crude oil futures transaction data used in this study comes from the Comprehensive Quotes and Graphics (CQG), an official NYMEX data vendor.

2.4.3 Firm-Specific News Releases

The sample period of August and September 2006 has been chosen because it contains several days on which regular company announcements were made, a few days when unscheduled "interesting announcements" were released and several control (non-announcement) days. News releases such as monthly traffic reports, fare increases, launches of new air routes and CEO changes are included in the sample, together with news stories related to the August 2006 U.K. terror plot. Company announcements data has been collected from the NYSE website (`http://www.nyse.com`). The NYSE provides market participants with the latest company Securities and Exchange Commission

Table 2.2: Firm-Specific News Releases

	Aug'06	Sep'06
AMR Corporation		
Analyst Reports	6	0
Earnings Related News	8	4
Security Related News	16	1
Marketing Announcements	10	6
Other Releases	2	3
U.S. Airways Group		
Analyst Reports	1	0
Earnings Related News	2	1
Security Related News	5	0
Marketing Announcements	1	0
Other Releases	1	2
Southwest Airlines		
Analyst Reports	3	0
Earnings Related News	3	1
Security Related News	0	0
Marketing Announcements	0	0
Other Releases	3	0

Notes: This table lists types of firm-specific news announcements included in the study and the total number of releases made between 9.45 and 16.00 during the sample period from 01 August to 30 September 2006. *Data source*: NYSE.

(SEC) filings, news stories and press releases, obtained from the Dow Jones Business News and PR Newswire. The time of the Dow Jones Business News announcements have been adjusted according to the dataset available from the Smith Barney webpage (`http://www.smithbarney.com`), where the identical news items are systematically published fifteen minutes earlier than on the NYSE. Information about the number of analysed announcements for each company is provided in Table 2.2.

There are forty two AMR related releases in August 2006, ten for U.S. Airways Group, and nine for Southwest Airlines. The sample sizes for September 2006 are considerably smaller, with fourteen, three and one releases for AMR, LCC and LUV, respectively. However, few announcements are recorded for June and July 2006, which implies that the August 2006 activity was higher than usual. In our empirical analysis, we partition firm-specific news into five groups: analyst reports, earnings related releases (such as new routes and fare announcements, or traffic reports), security related news, marketing announcements and others. We then study the effect of each announcement individually and jointly with the other releases of the same type.

2.4.4 Macroeconomic Announcements

There is extensive literature on macroeconomic factors that help to model and predict business cycles. When choosing variables that parsimoniously approximate macroeconomic activities, Sims (1980) suggests using a relatively small set of two output measures (real GNP and unemployment), three price indicators (the implicit price deflator for nonfarm business income, hourly compensation per worker and import prices) and a money sector measure (the M1 series). However, investors seem to react to more than just six macroeconomic news releases, and in event studies authors tend to use the widest possible set of macroeconomic announcements. Examples include Dwyer and Hafer (1989), Balduzzi et al. (2001), Hautsch and Hess (2002), Nofsinger and Prucyk (2003), Andersen et al. (2003) and Albuquerque and Vega (2006). We follow their approach and include all of the most influential announcements made by the U.S. federal agencies. To determine the initial set of potentially "influential," or price sensitive announcements, we follow Goldman Sachs's (2008) classifications of "medium" and "high" impact for news released during NYSE trading hours. Table 2.3 lists the macroeconomic statistics that are considered in this study along with the sample sizes (the partitioning follows Goldman Sachs, 2008).

It should be noted that several federal agencies release key macroeconomic statistics at 08.30 (i.e. outside the NYSE trading hours). The implication is that the effects of announcing inflation indicators, unemployment figures and GDP growth are not included in the present analysis. Such announcements could be analysed in the context of equity futures markets which are open when these releases are made. Dungey et al. (2008a) show that news releases that occur outside of the normal trading hours are absorbed by the equity markets via the electronic equity futures markets, such as the Global Exchange (GLOBEX) Trading System.

In addition to macroeconomic indicators, we include announcements about outcomes of the U.S. Treasury Bill auctions, since existing studies document that interest rates and interest rate spreads can predict the business cycle (see Harvey, 1988). Moreover, Stock and Watson (1989) find that

Table 2.3: U.S. Macroeconomic News Announcements

Announcement	Source[a]	Aug'06	Sep'06
Production, Orders & Inventories			
ISM Manufacturing Index	ISM	1	1
ISM Non-Manufacturing Index	ISM	1	1
Business Barometer Index	NAPM	1	1
Business Outlook	PhilFED	1	1
National Activity Index	ChFED	1	1
"Beige Book"	FRB	1	1
Crude Oil Inventories Report	EIA	5	5
Natural Gas Report	EIA	5	4
Consumer Spending & Confidence			
Consumer Confidence Index	CB	1	1
Consumer Sentiment Index	UM	1	3
Housing & Construction			
New Single-Family Home Sales	DC	1	1
Existing Home Sales	NAR	1	1
Pending Home Sales Index	NAR	1	1
Housing Market Index	NAHB/WF	1	1
Federal Reserve Policy			
Target Federal Funds Rate	FRB	1	1
Federal Government Finance			
Treasury Bill Auctions	DT	9	8
Treasury Bond Auctions	DT	5	3

Notes: This table lists the U.S. macroeconomic news announcements included in the study and the total number of releases made during the sample period from 01 August to 30 September 2006. The grouping follows Goldman Sachs (2008). *Data source*: Bloomberg.

[a] Conference Board(CB), Department of Commerce (DC), Department of Treasury (DT), Energy Information Administration (EIA), Federal Reserve Bank of Chicago (ChFED), Federal Reserve Bank of Philadelphia (PhilFED), Federal Reserve Board (FRB), Institute for Supply Management (ISM), National Association of Home Builders/Wells Fargo (NAHB/WF), National Association of Purchasing Managers Chicago (NAPM), National Association of Realtors (NAR), University of Michigan (UM).

two interest rate spreads—the difference between the six-month commercial paper rate and the six-month Treasury bill rate, and the difference between the ten-year and one-year Treasury bond rates—are important in their newly constructed index of leading economic indicators.

A few forward-looking indices are included in the announcement data. There are two consumer confidence measures—the University of Michigan Consumer Sentiment Index (reported as useful in predicting current changes in consumer purchasing behaviour by Carroll et al., 1994), and the Conference Board's Consumer Confidence Index (found to have asymmetric effects on the returns and volatility of the Dow Jones Industrial Average by Gulley and Sultan, 1998). We also analyse the effects of two national surveys of purchasing managers, the ISM National Manufacturing Index and the ISM National Non-Manufacturing (Services) Index. In addition, we include the Chicago Fed National Activity Index (CFNAI), Philadelphia Fed Business Outlook Survey and the Business Barometer Index published by the National Association of Purchasing Managers in Chicago.

We analyse *periods* before, during and after the announcements are made. We would prefer to follow Dwyer and Hafer (1989), Damodaran (1989), Balduzzi et al. (2001) and Andersen et al. (2003) and analyse the effect of *unexpected news*, defined as the difference between expected and actual announcements. These studies use consensus specialist forecasts as proxies for market expectations regarding scheduled macroeconomic releases. However, the majority of company announcements are not quantitative (with the exception of earnings announcements), which implies that the reliable decomposition into expected and unexpected components for both government and company announcements is not feasible. Therefore, our news indicators simply record that a news event has occurred. In this aspect, our study is similar to DeGennaro and Shrieves (1997), Ederington and Lee (2001) and Chang and Taylor (2003).

2.5 Empirical Results

2.5.1 ACH Estimates

The empirical analysis focuses on modelling the probability of a trade occurring within one-second intervals. This ultra-microstructure approach is dictated by the data: all three stocks are frequently traded and about a fifth of all trade durations are equal to one second. The average trade duration ranges between 7.3 and 10.5 seconds. Working with one-second intervals allows us to precisely estimate the effect of information arrival on market activity. However, this precision comes at a cost, as the dataset grows from an average of 108,407 tick-by-tick observations over the two month period to 967,500 one-second observations.

We model the observed data, which has not been diurnally adjusted. Following Engle and Russell (1998), empirical researchers often choose to first filter out the deterministic time-of-the-day effects, using either cubic splines (*inter alia* Engle and Russell, 1998, and Bauwens and Giot, 1998) or Fourier flexible form (Andersen and Bollerslev, 1997a and 1998). However, this approach is not feasible in cases such as this, in which the dependent variable is binary. Thus we model the deterministic and stochastic concurrently, with a uniform set of four time indicators employed to account for the intradaily seasonality in a parsimonious way. The time indicators are selected by the Bayesian Information Criterion (BIC). Table 2.4 reports results for the baseline model, i.e. the univariate ACH(1,1) with four time indicators, specified as

$$h_t = \left[\omega + \alpha_1 u_{N(t-1)} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t \in \tau(j)} \right]^{-1}, \qquad (2.10)$$

where $I_{t\in\tau(j)}$ denotes the time indicators and j = (9:45–10:59), (11:00–11:59), (12:00–13:59) and (14:00–14:59). Different specifications of time indicators and time periods, though not reported, yield very similar α_1 and β_1 estimates, but slightly worse BIC statistics overall.

The obtained parameter estimates are all statistically significant (a quasi-maximum likelihood estimator is applied to obtain robust standard errors) and similar to coefficients reported in intraday GARCH and ACD studies, with infrequent updating (small α_1), long memory in expected conditional hazards (β_1 close to one) and considerable persistence ($\alpha_1 + \beta_1$ very close to one). Andersen et al. (2007b), who use the ACH(1,1) model to study the occurrence of jumps in five-minute financial returns, report similar coefficients, though their β_1's are somewhat smaller. As in Hamilton and Jordà (2002) and Andersen et al. (2007b), we find that the basic ACH(1,1) model seems adequate. It does a good job of predicting whether a trade will occur within the next time interval. The proportion of correct predictions is 58.52% for American Airlines, 60.85% for U.S. Airways Group and 57.07% for Southwest Airlines.

We employ the BIC selection criterion and likelihood ratio test to determine the duration lag structure and consequently decide to use the ACH(2,1) to model the data. We include the relative bid/ask spread, logarithmic trade volume and return in all equations (see Dacarogna et al., 2001, for definitions and stylized facts), to account for market microstructure effects. We also include returns of the current front-month NYMEX light sweet crude oil

Table 2.4: Parameter Estimates of ACH(1,1) Models with Time Indicators

	AMR	LCC	LUV
ω	**0.0008**	**0.0029**	**0.0043**
	[0.0002]	[0.0003]	[0.0008]
α_1	**0.0011**	**0.0011**	**0.0011**
	[0.0001]	[0.0001]	[0.0001]
β_1	**0.9985**	**0.9984**	**0.9981**
	[0.0001]	[0.0001]	[0.0002]
$I_{t\in(9:45-10:59)}$	**0.0006**	**0.0009**	**0.0021**
	[0.0001]	[0.0001]	[0.0002]
$I_{t\in(11:00-11:59)}$	**0.0014**	**0.0014**	**0.0028**
	[0.0001]	[0.0002]	[0.0004]
$I_{t\in(12:00-13:59)}$	**0.0013**	**0.0017**	**0.0034**
	[0.0001]	[0.0002]	[0.0005]
$I_{t\in(14:00-14:59)}$	**0.0006**	**0.0006**	**0.0014**
	[0.0001]	[0.0002]	[0.0003]
lnL	-379,362.9	-299,134.6	-317,801.7
BIC	758,822.3	598,365.7	635,699.9
CorrPredict[a]	58.52%	60.85%	57.07%

Notes: We model the conditional probability of trade (h_t) in stocks of AMR Corporation (AMR), U.S. Airways Group (LCC) and Southwest Airlines (LUV) as

$$h_t = \left[\omega + \alpha_1 u_{N(t-1)} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}\right]^{-1},$$

where $I_{t\in\tau(j)}$ denotes time indicators. Coefficient estimates provided in **bold** are significant at the 5% level. Robust standard errors are provided in square brackets. The sample consists of 967,500 one-second observations based on NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ database.

[a] *CorrPredict* refers to the proportion of correct predictions from the model that a trade occurs within the next time interval.

futures contract. Table 2.5 reports parameter estimates for the univariate ACH(2,1) model with crude oil futures returns, market microstructure variables and time indicators, i.e.

$$\begin{aligned} h_t = \Bigg[&\omega + \alpha_1 u_{N(t-1)} + \alpha_2 u_{N(t-1)-1} + \beta_1 \psi_{t-1} \\ &+ \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)} + \delta \mathbf{z}_{t-1}\Bigg]^{-1}, \end{aligned} \tag{2.11}$$

where $\mathbf{z}_{t-1}$ denotes a vector of market microstructure covariates and crude oil futures returns. The market microstructure covariates at time $t-1$ are assumed to be equal to their value at the last observed trade t_{n-1}. Crude oil futures returns at time $t-1$ are equal to their most recent value at that time. This model has both a better likelihood and better BIC statistic than the baseline ACH(1,1). Further, it predicts more precisely whether or not a trade will occur within the next second. The proportion of correct predictions is 58.87% for American Airlines, 60.90% for U.S. Airways Group and 57.56% for Southwest Airlines.

The model provides an accurate approximation to trade frequency dynamics, as documented in Figure 2.4 (the top panel) that plots the average observed and fitted hazard rates. The diagnostic analysis of the standardized binary residuals, defined as

$$\hat{\varepsilon}_t = \frac{x_t - \hat{h}_t}{\sqrt{\hat{h}_t \cdot \left(1 - \hat{h}_t\right)}}, \tag{2.12}$$

indicates that the model accounts for the diurnal seasonality and almost all of the dynamic dependencies in the data (see the other panels of Figure 2.4).

Market microstructure variables have a small yet significant effect on trading frequency, with trade volume and price changes revealing more information than the relative bid/ask spread. The coefficients on the past trade volume are negative and strongly significant for all stocks, which implies that a higher volume per trade shortens the next conditional duration. This is consistent with the Easley and O'Hara (1992) model and previous empirical results of Bauwens and Giot (2000), Dufour and Engle (2000b) and Dungey et al. (2008b). However, in contrast to predictions from the Easley and O'Hara (1992) model, but consistent with the Admati and Pfleiderer (1988) model, we find that trades are more likely to occur as the bid/ask spread narrows. This finding is in line with Dow (2005), who shows that the wide bid/ask spread is associated with a decline in trading intensity, and with Dufour and Engle (2000b), whose empirical findings also imply that if there is any relationship between trade durations and bid/ask spread, it is positive, but statistically weak. The evidence concerning the dynamic relationship of returns and trade frequency is mixed. The estimate for Southwest Airlines suggests that as prices rise, the conditional probability of trade significantly increases. This provides evidence in support of the Diamond and Verrecchia (1987) analysis, where positive returns are associated with shorter trade durations. However, opposite results are obtained for American Airlines and U.S. Airways Group.

We find that crude oil futures returns are significant in modelling

Table 2.5: Parameter Estimates of ACH(2,1) Models with Crude Oil Futures Returns, Market Microstructure Variables and Time Indicators

	AMR	LCC	LUV
ω	**0.0186**	**0.0442**	**0.0433**
	[0.0019]	[0.0049]	[0.0092]
α_1	**0.0009**	**0.0010**	**0.0013**
	[0.0001]	[0.0001]	[0.0002]
α_2	**0.0010**	**0.0010**	**0.0011**
	[0.0001]	[0.0001]	[0.0002]
β_1	**0.9973**	**0.9968**	**0.9953**
	[0.0002]	[0.0003]	[0.0009]
oil_{t-1}	**-0.0007**	**-0.0017**	0.0001
	[0.0002]	[0.0003]	[0.0004]
$return_{t-1}$	**0.0023**	**0.0124**	**-0.0160**
	[0.0012]	[0.0024]	[0.0071]
$volume_{t-1}$	**-0.0030**	**-0.0061**	**-0.0069**
	[0.0003]	[0.0006]	[0.0013]
$spread_{t-1}$	0.0001	**0.0028**	**0.0030**
	[0.0001]	[0.0004]	[0.0006]
$I_{t\in(9:45-10:59)}$	**0.0005**	0.0005	**0.0021**
	[0.0001]	[0.0003]	[0.0002]
$I_{t\in(11:00-11:59)}$	**0.0015**	**0.0014**	**0.0049**
	[0.0002]	[0.0003]	[0.0012]
$I_{t\in(12:00-13:59)}$	**0.0018**	**0.0024**	**0.0071**
	[0.0002]	[0.0004]	[0.0019]
$I_{t\in(14:00-14:59)}$	**0.0006**	0.0006	**0.0028**
	[0.0002]	[0.0003]	[0.0010]
lnL	-378,707.3	-298,157.2	-317,386.1
LR stat[a]	**1,311.2**	**1,954.8**	**831.2**
BIC	757,579.9	596,479.8	634,937.5
CorrPredict[a]	58.87%	60.90%	57.56%

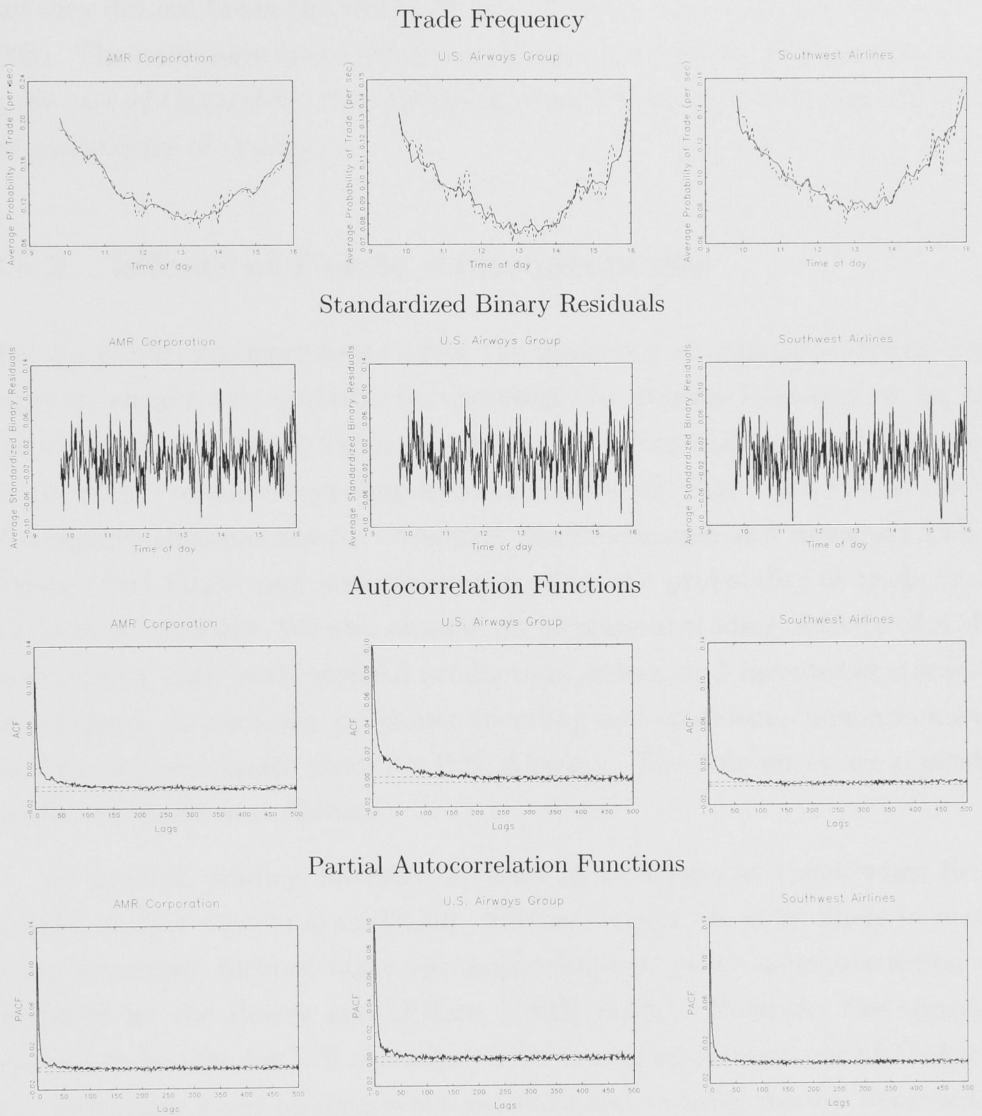
Notes: We model the conditional probability of trade (h_t) in stocks of AMR Corporation (AMR), U.S. Airways Group (LCC) and Southwest Airlines (LUV) as

$$h_t = \left[\omega + \alpha_1 u_{N(t-1)} + \alpha_2 u_{N(t-1)-1} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)} + \delta \mathbf{z}_{t-1}\right]^{-1},$$

where $I_{t\in\tau(j)}$ denotes time indicators and $\mathbf{z}_{t-1}$ denotes a vector of exogenous covariates: *oil* (the current month NYMEX light sweet crude oil futures returns), *return* (the return constructed from the share price series), *volume* (the logarithm of the number of shares traded), and *spread* (the relative bid/ask spread). All covariates have been scaled to have unit variances. Coefficient estimates provided in **bold** are significant at the 5% level. Robust standard errors are provided in square brackets. The sample consists of 967,500 one-second observations based on NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ and CQG databases.

[a] The *LR statistic* tests the joint significance of the variables *not* included in the baseline ACH(1,1) model (Table 2.4) and follows χ^2 (5) under H_0. Statistics provided in **bold** are significant at 5% level. *CorrPredict* refers to the proportion of correct predictions from the model that a trade occurs within the next time interval.

Figure 2.4: Model Diagnostics for ACH(2,1) Models



Notes: The first panel represents the fitted and observed average intraday patterns of trade frequency (the solid and dashed lines, respectively). The averages are based on five-minute intervals of trading activity. The next three panels provide diagnostics of the standardized binary residuals: the fitted intraday patterns (second panel), the ACF for the first 500 lags (third panel), and the PACF for the first 500 lags (fourth panel). The fourth panel inserts illustrate the PACF for the first 100 lags of standardized binary residuals. The dashed lines represent 95% confidence bounds. The relevant parameter estimates are reported in Table 2.5. The time between trades is measured in seconds and the time of the day is measured in hours since midnight. The sample consists of NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ database.

the frequency of trading in AMR and LCC stocks, with higher crude oil futures prices significantly increasing hazard rates. This result confirms those of Sadorsky (1999) and Papapetrou (2001), who find that crude oil price movements are important in modelling monthly stock returns. However, for Southwest Airlines we consistently find no significant short-run spillovers from crude oil futures markets. Interestingly, Southwest Airlines are well known for their very effective "forward buy" jet-fuel futures program (Mandaro, 2008), and they did not break the USD 1.00 per US gallon threshold until 2008 (Cox, 2005). The immunisation to short-run changes in crude oil prices implies that, in the case of this airline, the changes in crude oil futures returns do not affect the probability of trading.

2.5.2 Effects of Public Announcements

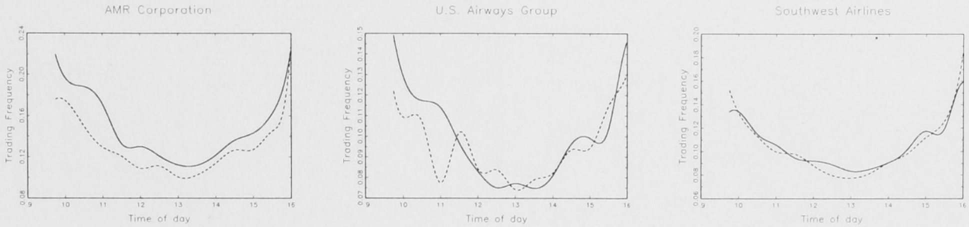
How do public announcements affect the frequency of trading in stocks? We begin to answer this question by analysing the average hazard rates during particular announcement and non-announcement (control) days (see Figure 2.5 for the effects of macroeconomic announcements and Figure 2.6 for the effects of company announcements). Amongst macroeconomic and monetary policy releases, Fed target rate announcements affect the probability of trade in all stocks most strongly. We also observe an increase in trading activity of AMR stock during days when sectoral production, orders, and inventories statistics are released. In contrast, consumer spending and confidence announcements tend to increase hazard rates for U.S. Airways. The differences are typically smaller for Southwest Airlines.

In general, trading intensity appears to be larger at times when firm-specific analyst reports are released. Further, trades are more likely to occur when American Airlines make earnings-related or other announcements, as predicted by the Easley and O'Hara (1992) model. However, the opposite appears to be true for U.S. Airways. In fact, trading intensity in LCC shares is considerably lower on days when earnings and security related releases are made.

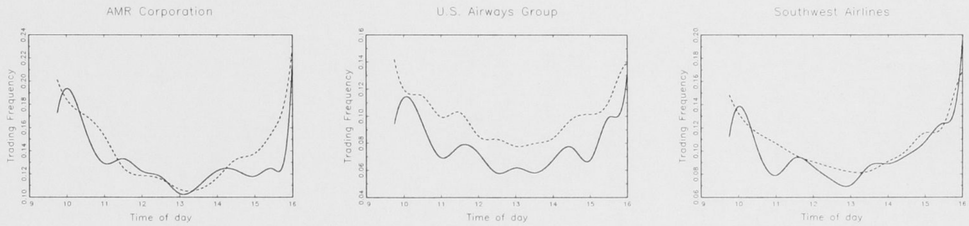
To study the short-run impact of news arrival on the probability of trade within the ACH framework, we include three announcement variables in equation (2.11), to denote observation windows of five minutes *before* an announcement ($A_{t,-1}$), the minute *during* which an announcement is made ($A_{t,0}$) and ten minutes *after* an announcement is made ($A_{t,1}$). Our choice of the lengths of observation windows is similar to Simonsen (2006), who studies the impact of news arrival on trade durations in Swedish stocks and reports that the 5-1-10 observation windows provide an adequate data fit as well as the largest number of significant parameters. As in Simonsen (2006), we find that

Figure 2.5: Effect of Macroeconomic Announcements on Trade Frequency

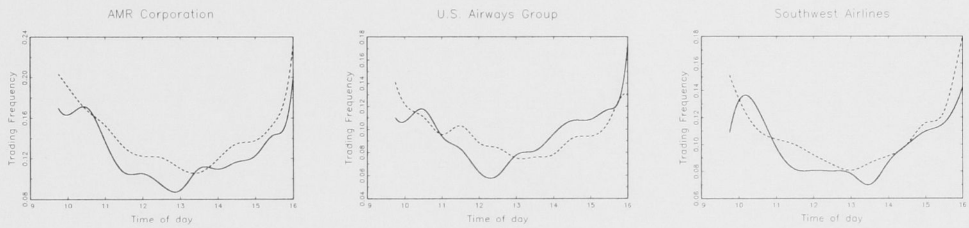
Sectoral Production, Orders, and Inventories



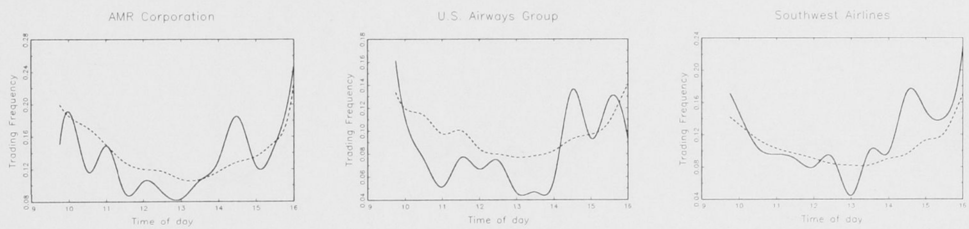
Consumer Spending and Confidence



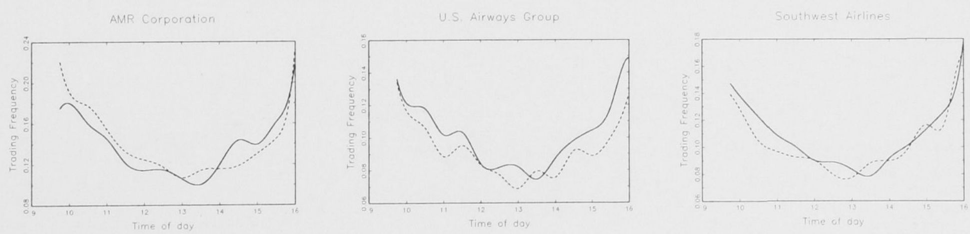
Housing and Construction



Federal Reserve Policy

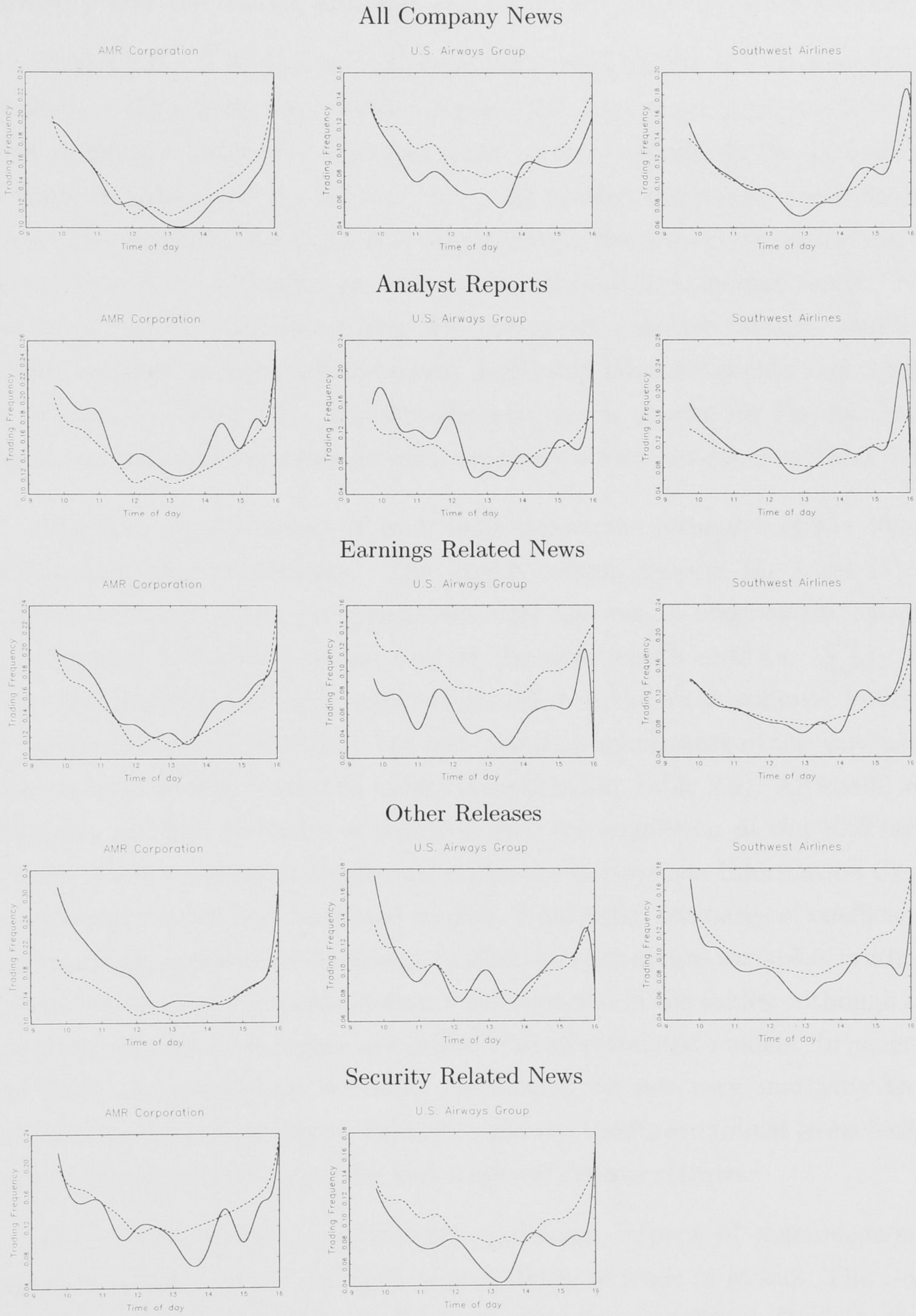


Federal Government Finance



Notes: The solid lines represent trading frequency for announcement days and the dashed lines represent trading frequency for days when no macroeconomic announcements of this type were made. Both estimates are obtained using cubic splines with half-hourly knots. The time between trades is measured in seconds and the time of the day is measured in hours since midnight. The sample consists of 967,500 one-second observations based on NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ database and Bloomberg.

Figure 2.6: Effect of Company Announcements on Trade Frequency



Notes: The solid lines represent trading frequency for announcement days and the dashed lines represent trading frequency for days when no firm-specific releases were made. Both estimates are obtained using cubic splines with half-hourly knots. The time between trades is measured in seconds and the time of the day is measured in hours since midnight. The sample consists of 967,500 one-second observations based on NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ database and NYSE.

changing the before-during-after time intervals to 15-5-20 minutes does not markedly vary the results, although less significant coefficients are obtained.

Tables 2.6 – 2.10 present the empirical results for the 5-1-10 observation windows. The first three tables report the impact of grouped and the most significant individual macroeconomic announcements on the probability of trade in airline stocks. Tables 2.9 – 2.10 present the results for company news. The results in Table 2.9 show the average effect of any company release on the frequency of trading as well as the effect of firm-specific news. This has been further partitioned into five categories (analyst reports, earnings related releases, security related news, marketing announcements and others, as detailed in Table 2.2). Finally, the estimation results for the five most significant individual releases for each company are summarized in Table 2.10.

The first three columns of each table report the estimates of the *before*, *during* and *after* coefficients. The fourth column reports the total (accumulative) impact of an announcement over the entire observation window (16 minutes), calculated as the sum of the news coefficients i.e. $\sum_{\tau=-1}^{1} \theta_{\tau}$. The total likelihood of each model is provided in the sixth column, followed by the likelihood ratio statistic that tests the joint significance of the announcement indicators (the restricted model is reported in Table 2.5). All coefficient estimates and test statistics provided in bold are significant at the 10% level. Finally, the last column indicates the difference in Bayesian Information Criteria between the full and restricted models. Parameter estimates of coefficients for durations, conditional durations, market microstructure variables, crude oil futures returns and time indicators are not reported in the tables, although the relevant explanatory variables are included in all estimated models. In general, the ACH and exogenous covariate coefficients do not vary markedly from the baseline values reported in Table 2.5, and the results are robust to excluding market microstructure variables and crude oil futures returns.

Our results reveal a statistically significant impact of macroeconomic information flows on the conditional probability of trade in stocks. The Business Barometer Index, Current Economic Conditions ("Beige Book"), Consumer Sentiment Index, Federal Reserve Policy announcements and the results of Treasury Bond auctions have a considerable and mostly positive impact on the frequency of trading in all three stocks (the median behaviour of trading frequency in the presence of these macroeconomic releases is presented in Figure 2.7). Other macroeconomic indicators significantly affect the hazard

Table 2.6: Impact of Macroeconomic Announcements on the Probability of Trade in AMR Corporation Stock

	Before	During	After	Total[a]	lnL	LR stat[a]	BIC diff[a]
Production, Orders & Inventories	-0.0008	**-0.0106**	-0.0003	**-0.0116**	-378,688.1	**38.4**	3.0
ISM Manufacturing Index	**-0.0082**	**0.0249**	0.0003	0.0169	-378,702.0	**10.5**	30.9
ISM Non-Manufacturing Index	-0.0040	-0.0035	-0.0017	-0.0092	-378,700.0	**14.5**	26.9
Business Barometer Index	**0.0121**	-0.0345	0.0021	-0.0203	-378,702.4	**9.8**	31.6
"Beige Book"	-0.0002	**-0.0519**	0.0002	**-0.0519**	-378,703.3	**7.9**	33.5
Crude Oil Inventories Report	-0.0017	**-0.0093**	**-0.0009**	**-0.0120**	-378,687.4	**39.8**	1.6
Natural Gas Report	0.0017	**-0.0203**	**0.0016**	**-0.0169**	-378,702.6	**9.3**	32.0
Consumer Spending & Confidence	**-0.0097**	0.0034	-0.0002	-0.0065	-378,697.8	**19.0**	22.4
Consumer Confidence Index	0.0051	**-0.0656**	-0.0010	**-0.0615**	-378,685.5	**43.6**	-1.9
Consumer Sentiment Index	– – –	**0.0125**	0.0004	**0.0129**	-378,703.9	**6.8**	20.7
Housing & Construction	-0.0028	-0.0003	0.0005	-0.0026	-378,705.5	3.5	37.9
New Single-Family Home Sales	**0.0156**	**-0.0933**	**0.0047**	**-0.0730**	-378,697.9	**18.8**	22.5
Existing Home Sales	-0.0009	0.0197	-0.0037	0.0151	-378,705.7	3.2	38.2
Federal Reserve Policy (Target Rate)	**-0.0124**	-0.0111	0.0023	**-0.0212**	-378,690.4	**33.7**	7.6
Federal Government Finance	0.0023	-0.0099	**0.0021**	-0.0055	-378,703.6	**7.4**	34.0
Treasury Bill Auctions	-0.0018	-0.0005	0.0010	-0.0014	-378,706.5	1.4	39.9
Treasury Bond Auctions	**0.0069**	-0.0215	**0.0046**	-0.0100	-378,698.9	**16.8**	24.5

Notes: We model the conditional probability of trade (h_t) in AMR Corporation stock as

$$h_t = \left[\omega + \alpha_1 u_{N(t-1)} + \alpha_2 u_{N(t-1)-1} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)} + \delta \mathbf{z}_{t-1} + \sum_{\tau=-1}^{1} \theta_\tau A_{t,\tau}\right]^{-1},$$

where $A_{t,-1}$ indicates the five-minute period *before* an announcement, $A_{t,0}$—the minute *during* which an announcement has occurred and $A_{t,1}$—the ten-minute period *after* an announcement. Parameter estimates of durations, conditional durations, exogenous covariates $\mathbf{z}_{t-1}$ and time indicators $I_{t\in\tau(j)}$ are not reported in the table, although they were included in the estimated models. Coefficient estimates provided in **bold** are significant at the 10% level (robust standard errors). The sample consists of 967,500 one-second observations based on NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ and CQG databases, Bloomberg.

[a] *Total* denotes the total impact of an announcement, calculated as $\sum_{\tau=-1}^{1}\theta_\tau$ and tested for significance using a χ^2 (1) statistic. The *LR statistic* tests the joint significance of the announcement indicators (the restricted model is reported in Table 2.5) and follows χ^2 (3) under H_0. Statistics provided in **bold** are significant at 10% level. *BIC diff* indicates the difference in BIC between the full and restricted models, i.e. *BIC diff* = *BIC full* − *BIC restricted*.

Table 2.7: Impact of Macroeconomic Announcements on the Probability of Trade in U.S. Airways Group Stock

	Before	During	After	Total[a]	lnL	LR stat[a]	BIC diff[a]
Production, Orders & Inventories	**0.0043**	**-0.0309**	-0.0006	**-0.0272**	-298,147.9	**18.6**	22.8
ISM Manufacturing Index	0.0041	0.0421	**-0.0059**	0.0403	-298,154.6	5.1	36.2
ISM Non-Manufacturing Index	-0.0019	0.0418	-0.0024	0.0376	-298,156.2	1.8	39.5
Business Barometer Index	-0.0028	**-0.0555**	0.0030	**-0.0552**	-298,153.6	**7.3**	34.0
"Beige Book"	**0.1439**	**-0.5028**	0.0225	**-0.3363**	-298,149.4	**15.7**	25.7
Crude Oil Inventories Report	0.0028	**-0.0221**	-0.0020	**-0.0213**	-298,150.8	**12.9**	28.5
Natural Gas Report	0.0087	**-0.0599**	**0.0048**	**-0.0464**	-298,152.0	**10.3**	31.0
Consumer Spending & Confidence	0.0056	**0.0734**	**-0.0068**	**0.0722**	-298,147.2	**20.0**	21.3
Consumer Confidence Index	0.0080	0.0594	**-0.0090**	0.0584	-298,153.8	**6.8**	34.6
Consumer Sentiment Index	– – –	**0.0738**	**-0.0063**	**0.0675**	-298,150.3	**13.9**	27.5
Housing & Construction	-0.0043	**0.0362**	**-0.0057**	0.0262	-298,149.6	**15.2**	26.1
New Single-Family Home Sales	**-0.0131**	0.0166	**-0.0036**	-0.0001	-298,151.1	**12.3**	29.0
Existing Home Sales	0.0180	0.0576	**-0.0221**	0.0535	-298,141.7	**31.0**	10.4
Federal Reserve Policy (Target Rate)	-0.0145	-0.0358	-0.0034	**-0.0537**	-298,147.4	**19.6**	21.7
Federal Government Finance	**0.0076**	**-0.0428**	**0.0037**	**-0.0316**	-298,151.8	**10.7**	30.6
Treasury Bill Auctions	-0.0018	**-0.0319**	0.0015	**-0.0322**	-298,153.3	**7.7**	33.6
Treasury Bond Auctions	**0.0259**	**-0.0806**	**0.0136**	-0.0411	-298139.0	**36.4**	4.9

Notes: We model the conditional probability of trade (h_t) in U.S. Airways Group stock as

$$h_t = \left[\omega + \alpha_1 u_{N(t-1)} + \alpha_2 u_{N(t-1)-1} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)} + \delta \mathbf{z}_{t-1} + \sum_{\tau=-1}^{1} \theta_\tau A_{t,\tau}\right]^{-1},$$

where $A_{t,-1}$ indicates the five-minute period *before* an announcement, $A_{t,0}$—the minute *during* which an announcement has occurred and $A_{t,1}$—the ten-minute period *after* an announcement. Parameter estimates of durations, conditional durations, exogenous covariates $\mathbf{z}_{t-1}$ and time indicators $I_{t\in\tau(j)}$ are not reported in the table, although they were included in the estimated models. Coefficient estimates provided in **bold** are significant at the 10% level (robust standard errors). The sample consists of 967,500 one-second observations based on NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ and CQG databases, Bloomberg.

[a] *Total* denotes the total impact of an announcement, calculated as $\sum_{\tau=-1}^{1} \theta_\tau$ and tested for significance using a $\chi^2(1)$ statistic. The *LR statistic* tests the joint significance of the announcement indicators (the restricted model is reported in Table 2.5) and follows $\chi^2(3)$ under H_0. Statistics provided in **bold** are significant at 10% level. *BIC diff* indicates the difference in BIC between the full and restricted models, i.e. *BIC diff = BIC full − BIC restricted*.

Table 2.8: Impact of Macroeconomic Announcements on the Probability of Trade in Southwest Airlines Stock

	Before	During	After	Total[a]	lnL	LR stat[a]	BIC diff[a]
Production, Orders & Inventories	-0.0002	**-0.0148**	0.0005	**-0.0145**	-317,383.2	5.8	35.5
ISM Manufacturing Index	**-0.0147**	0.0179	**-0.0055**	**-0.0024**	-317,381.5	**9.1**	32.2
ISM Non-Manufacturing Index	-0.0020	-0.0153	0.0037	-0.0137	-317,385.5	1.2	40.2
Business Barometer Index	**-0.0111**	-0.0304	**0.0089**	**-0.0327**	-317,380.2	**11.7**	29.7
"Beige Book"	0.0012	-0.1532	0.0164	-0.1355	-317,380.0	**12.2**	29.2
Crude Oil Inventories Report	-0.0019	-0.0080	0.0005	-0.0093	-317,385.1	1.9	39.4
Natural Gas Report	0.0069	-0.0205	0.0021	-0.0115	-317,384.3	3.4	37.9
Consumer Spending & Confidence	-0.0033	**0.0411**	**-0.0050**	**0.0328**	-317,381.6	**8.9**	32.4
Consumer Confidence Index	0.0010	-0.0009	-0.0042	-0.0041	-317,385.1	1.9	39.5
Consumer Sentiment Index	– – –	**0.0584**	**-0.0053**	**0.0531**	-317,381.0	**10.2**	31.2
Housing & Construction	**-0.0124**	0.0231	**-0.0042**	0.0066	-317,379.4	**13.3**	28.0
New Single-Family Home Sales	**-0.0221**	**0.0700**	**-0.0080**	0.0400	-317,377.6	**16.9**	24.5
Existing Home Sales	0.0147	-0.0718	0.0022	**-0.0549**	-317,386.0	0.0	41.4
Federal Reserve Policy (Target Rate)	**-0.0369**	-0.0224	**-0.0053**	**-0.0646**	-317,344.6	**82.9**	-41.6
Federal Government Finance	**0.0086**	**-0.0424**	**0.0120**	**-0.0218**	-317,364.8	**42.5**	-1.1
Treasury Bill Auctions	**0.0078**	**-0.0346**	**0.0117**	-0.0150	-317,371.9	**28.3**	13.1
Treasury Bond Auctions	0.0121	**-0.0767**	**0.0155**	**-0.0491**	-317,377.3	**17.6**	23.8

Notes: We model the conditional probability of trade (h_t) in Southwest Airlines stock as

$$h_t = \left[\omega + \alpha_1 u_{N(t-1)} + \alpha_2 u_{N(t-1)-1} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)} + \delta \mathbf{z}_{t-1} + \sum_{\tau=-1}^{1} \theta_\tau A_{t,\tau}\right]^{-1},$$

where $A_{t,-1}$ indicates the five-minute period *before* an announcement, $A_{t,0}$—the minute *during* which an announcement has occurred and $A_{t,1}$—the ten-minute period *after* an announcement. Parameter estimates of durations, conditional durations, exogenous covariates $\mathbf{z}_{t-1}$ and time indicators $I_{t\in\tau(j)}$ are not reported in the table, although they were included in the estimated models. Coefficient estimates provided in **bold** are significant at the 10% level (robust standard errors). The sample consists of 967,500 one-second observations based on NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ and CQG databases, Bloomberg.

[a] *Total* denotes the total impact of an announcement, calculated as $\sum_{\tau=-1}^{1}\theta_\tau$ and tested for significance using a $\chi^2(1)$ statistic. The *LR statistic* tests the joint significance of the announcement indicators (the restricted model is reported in Table 2.5) and follows $\chi^2(3)$ under H_0. Statistics provided in **bold** are significant at 10% level. *BIC diff* indicates the difference in BIC between the full and restricted models, i.e. *BIC diff = BIC full − BIC restricted*.

Table 2.9: Impact of Firm-Specific News Releases (*by Genre*) on the Probability of Trade

	Before	During	After	Total[a]	lnL	LR stat[a]	BIC diff[a]
AMR Corporation							
All Company News	0.0011	**-0.0067**	0.0005	-0.0051	-378,705.2	4.2	37.1
Analyst Reports	-0.0019	0.0064	-0.0002	0.0043	-378,706.8	0.9	40.5
Earnings Related News	0.0016	-0.0082	0.0012	-0.0055	-378,705.2	4.2	37.1
Security Related News	0.0018	-0.0043	0.0003	-0.0023	-378,706.2	2.2	39.2
Other Releases	**0.0074**	-0.0181	-0.0006	-0.0113	-378,705.1	4.4	36.9
U.S. Airways Group							
All Company News	0.0077	-0.0052	0.0047	0.0071	-298,151.9	**10.6**	30.8
Analyst Reports	**-0.0202**	**0.1116**	0.0005	0.0919	-298,154.6	5.2	36.1
Earnings Related News	0.0224	-0.0226	**0.0321**	0.0318	-298,145.9	**22.6**	18.8
Security Related News	**0.0320**	0.0460	0.0091	0.0871	-298,137.4	**39.6**	1.7
Other Releases	-0.0055	-0.0497	-0.0044	**-0.0596**	-298,146.6	**21.2**	20.2
Southwest Airlines							
All Company News	**-0.0124**	**0.0792**	**-0.0152**	**0.0516**	-317,323.1	**125.9**	-84.5
Analyst Reports	**-0.0103**	0.0285	**-0.0201**	-0.0019	-317,256.6	**258.9**	-217.6
Earnings Related News	**-0.0146**	**0.0457**	0.0040	**0.0351**	-317,377.2	**17.7**	23.6
Other Releases	-0.0022	-0.0138	**0.0230**	0.0070	-317,376.6	**18.8**	22.5

Notes: We model the conditional probability of trade (h_t) in stocks of AMR Corporation, U.S. Airways Group and Southwest Airlines as

$$h_t = \left[\omega + \alpha_1 u_{N(t-1)} + \alpha_2 u_{N(t-1)-1} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)} + \delta \mathbf{z}_{t-1} + \sum_{\tau=-1}^{1} \theta_\tau A_{t,\tau}\right]^{-1},$$

where $A_{t,-1}$ indicates the five-minute period *before* an announcement, $A_{t,0}$—the minute *during* which an announcement has occurred and $A_{t,1}$—the ten-minute period *after* an announcement. Parameter estimates of durations, conditional durations, exogenous covariates $\mathbf{z}_{t-1}$ and time indicators $I_{t\in\tau(j)}$ are not reported in the table, although they were included in the estimated models. Coefficient estimates provided in **bold** are significant at the 10% level (robust standard errors). Insignificant results for AMR and LCC marketing announcements are not reported. The sample consists of 967,500 one-second observations based on NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ and CQG databases, NYSE.

[a] *Total* denotes the total impact of an announcement, calculated as $\sum_{\tau=-1}^{1} \theta_\tau$ and tested for significance using a $\chi^2(1)$ statistic. The *LR statistic* tests the joint significance of the announcement indicators (the restricted model is reported in Table 2.5) and follows $\chi^2(3)$ under H_0. Statistics provided in **bold** are significant at 10% level. *BIC diff* indicates the difference in BIC between the full and restricted models, i.e. *BIC diff* = *BIC full* − *BIC restricted*.

Table 2.10: Impact of Most Significant Firm-Specific News Releases on the Probability of Trade

	Before	During	After	Total[a]	lnL	LR stat[a]	BIC diff[a]
AMR Corporation							
Earnings 04.08 11:00	**0.0224**	**0.1430**	0.0096	**0.1750**	-378,694.0	**26.4**	14.9
Security 10.08 15:30	**-0.0123**	**0.0300**	**0.0065**	**0.0241**	-378,695.7	**23.2**	18.2
Ticket Prices 18.08 12:10	0.0450	**-0.2664**	**0.0373**	**-0.1841**	-378,697.2	**20.1**	21.2
Security 10:08 10:05	0.0003	**0.0806**	-0.0042	0.0766	-378,697.6	**19.3**	22.0
Security 10:08 9:53	-0.0009	-0.0027	**0.0067**	0.0031	-378,698.0	**18.5**	22.8
U.S. Airways Group							
Ticket Prices 29.08 11:00	0.0610	0.3897	0.0477	0.4984	-298,135.0	**44.5**	-3.1
Other (New CEO) 14.09 11:30	**-0.0261**	-0.0102	-0.0039	**-0.0401**	-298,143.3	**27.9**	13.4
Security 10.08 12:57	0.0208	0.0856	0.0278	0.1341	-298,146.1	**22.2**	19.1
New Routes 22.09 14:44	**-0.0810**	0.0936	0.0161	0.0287	-298,149.6	**15.1**	26.2
Security 25.08 15:16	-0.0613	0.1228	**0.1130**	**0.1745**	-298,150.7	**13.0**	28.4
Southwest Airlines							
Analyst Report 03.08 15:34	0.0324	**-0.1131**	**-0.0223**	**-0.1030**	-317,203.0	**366.2**	-324.8
Ticket Prices 12.09 10:00	-0.0205	0.0454	**0.0056**	**0.0304**	-317,373.3	**25.6**	15.8
Analyst Report 10.08 15:26	**-0.0208**	0.0391	**-0.0075**	0.0108	-317,373.3	**25.4**	15.9
Other (Energy Policies) 02.08 14:03	-0.0166	0.0106	**0.0262**	0.0203	-317,380.5	**11.2**	30.2
Other (New CEO) 30.08 15:00	0.0014	-0.0151	**0.0234**	0.0097	-317,382.1	**7.9**	33.4

Notes: We model the conditional probability of trade (h_t) in stocks of AMR Corporation, U.S. Airways Group and Southwest Airlines as

$$h_t = \left[\omega + \alpha_1 u_{N(t-1)} + \alpha_2 u_{N(t-1)-1} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)} + \delta \mathbf{z}_{t-1} + \sum_{\tau=-1}^{1} \theta_\tau A_{t,\tau}\right]^{-1},$$

where $A_{t,-1}$ indicates the five-minute period *before* an announcement, $A_{t,0}$—the minute *during* which an announcement has occurred and $A_{t,1}$—the ten-minute period *after* an announcement. Parameter estimates of durations, conditional durations, exogenous covariates $\mathbf{z}_{t-1}$ and time indicators $I_{t\in\tau(j)}$ are not reported in the table, although they were included in the estimated models. Coefficient estimates provided in **bold** are significant at the 10% level (robust standard errors). Analysed announcements are ordered by the total significance of the model. The sample consists of 967,500 one-second observations based on NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ and CQG databases, NYSE.

[a] *Total* denotes the total impact of an announcement, calculated as $\sum_{\tau=-1}^{1} \theta_\tau$ and tested for significance using a χ^2 (1) statistic. The *LR statistic* tests the joint significance of the announcement indicators (the restricted model is reported in Table 2.5) and follows χ^2 (3) under H_0. Statistics provided in **bold** are significant at 10% level. *BIC diff* indicates the difference in BIC between the full and restricted models, i.e. *BIC diff = BIC full − BIC restricted*.

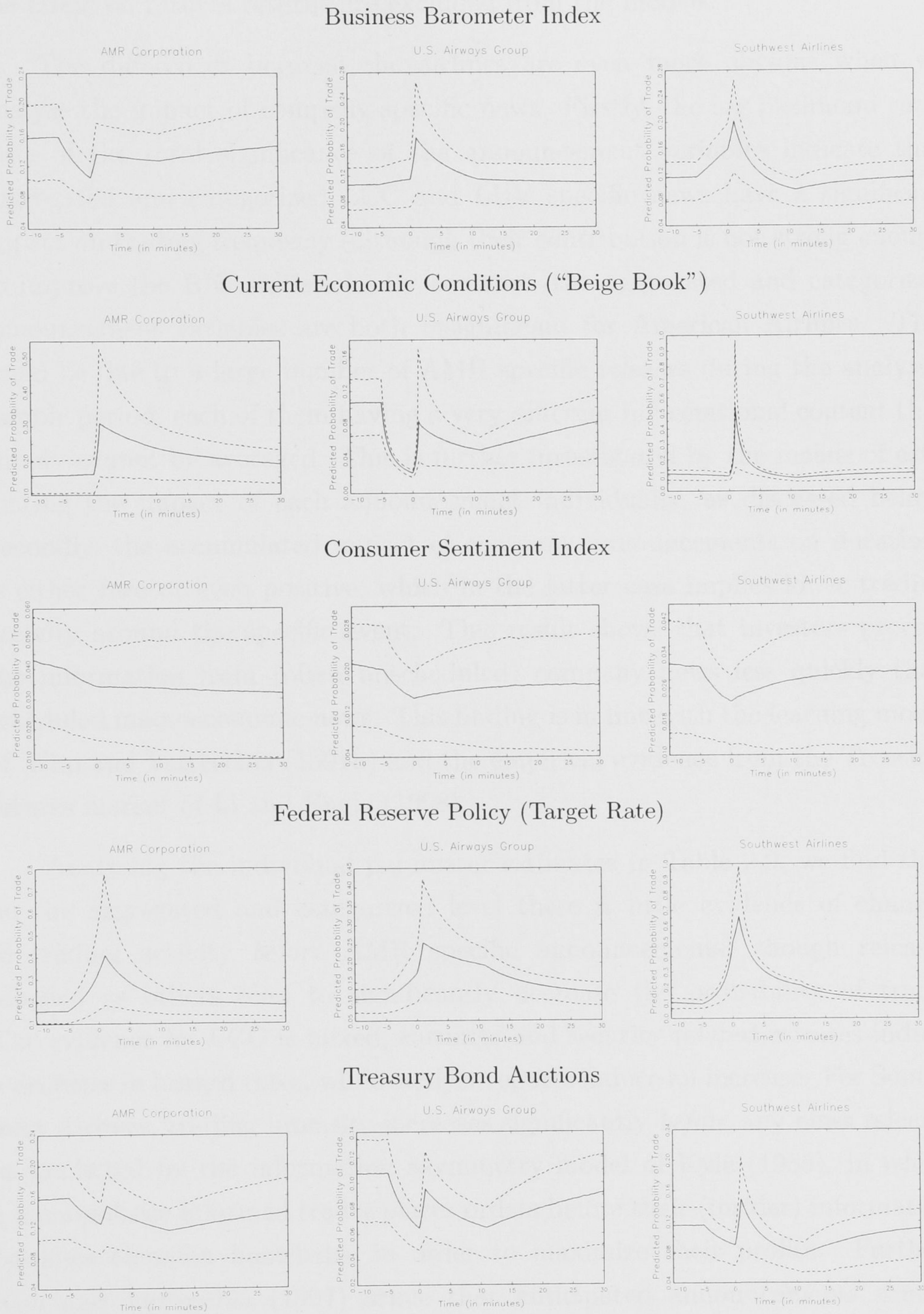
rates of at least one stock, as indicated by large likelihood ratio statistics that test the joint significance of the announcement indicators. The single exception is the release of the Housing Market Index, produced by the National Association of Home Builders/Wells Fargo, which had no impact on the frequency of trading in any stock during the analysed period. Whilst the inclusion of news arrival variables significantly increases the explanatory power of the ACH model, this contribution is usually not strong enough to improve the Bayesian Information Criterion.

Consistent with the market microstructure theory that investors trade on information (Easley and O'Hara, 1992), we find that macroeconomic news inflow induces a contemporaneous and cumulative increase in trading activity. On average, the estimates of the individual news indicator coefficients and their sums are negative, implying shorter trade durations and larger hazard rates over the entire observation window (16 minutes). Hazard rates usually return to their pre-announcement levels within about 30 minutes. For the set of indicators that positively affect all three stocks (see Figure 2.7), the likelihood of trades occurring during the release is two to six times greater than the usual likelihood of trades occurring. In particular, announcements of the Federal Reserve target rate induce a significant spike in the hazard rates of all stocks. This result is intriguing as during the analysed sample period the changes in monetary policy were in line with market expectations and as such "market efficiency would dictate that the expected portion of an announcement should have no impact" (Almeida et al., 1998).

It is also interesting to note that Crude Oil Inventories and Natural Gas Reports, published weekly by the Energy Information Administration, are good predictors of the probability of trade in AMR and LCC stocks, but not in LUV stock. This is in line with our observation that crude oil futures returns are insignificant when modelling the frequency of trading in LUV stock, and yet they matter when analysing the other airline shares.

Further, a careful look at coefficients of announcements that are released early suggests that timeliness matters to some extent. That is, statistics that are released shortly after the period they cover, such as the ISM Manufacturing Index or the Consumer Confidence Index, have a larger impact on the probability of trade than less timely indicators (see Fleming and Remolona, 1999, Andersen et al., 2003 and Veredas, 2006 for related evidence from fixed interest and foreign exchange rates markets). Finally, we find that

Figure 2.7: Trading Frequency Responses to Macroeconomic Announcements



Notes: The solid lines represent the median behaviour of trading frequency in the presence of macroeconomic releases, and the dashed lines represent the 95% confidence intervals. Both estimates are obtained using Monte Carlo simulations based on parameter estimates reported in Tables 2.6 – 2.8. The x-axis denotes time in minutes, with the announcement time fixed at 0. The sample consists of 967,500 one-second observations based on NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ database and Bloomberg.

the sign and significance of the announcement variables do not change when the crude oil futures returns are excluded from the models.

The differences between the airlines are even more obvious when we analyse the impact of company-specific news. Firstly, the log likelihood ratio tests of the total significance of the announcement variables indicate that aggregated and categorized LCC and LUV specific news have a significant impact on trading frequency (although their contribution is not strong enough to improve the BIC statistic). By contrast, the aggregated and categorized announcement variables are both insignificant for American Airlines. This could be due to a large number of AMR specific releases during the analysed sample period, each of them having a very different informational content that simply cannot be averaged. This is further investigated by the means of estimating the impact of each announcement individually, as discussed below. Secondly, the accumulated impact of company announcements on durations is either zero or even positive, which in the latter case implies lower trading activity around the specific event. This result shows that investors process the information from (often unscheduled) company news less quickly than scheduled macroeconomic news. This finding is in line with the learning model of Kim and Verrecchia (1991b) and the empirical evidence from the Treasury futures market of Li and Engle (1998).

Analysing the individual parameter estimates in Table 2.9, we find that on the aggregated and categorized level there is little evidence of changes in trading activity *before* AMR specific announcements, though releases labelled as others tend to significantly decrease the probability of trade. The evidence for LCC is mixed; earnings and security related releases induce a decrease in hazard rates, while analyst reports induce an increase. For Southwest Airlines, trading intensity increases significantly *before* any news release, as predicted by the information asymmetry model of Kyle (1985), in which a monopolistic informed trader places orders before their (insider) information becomes common knowledge in order to maximize their profits. Further, Kim and Verrecchia (1997) argue that anticipated announcements should induce higher pre-announcement activity than unanticipated announcements, and indeed all releases made by Southwest Airlines (apart from analyst reports) were publicly pre-advertised. By contrast, the information sets for the other two companies include many unanticipated "breaking news" stories, such as security releases concerning the terrorist threat at London airport (10 August 2006).

During an announcement itself traders often seem to "pause" (indicated by positive coefficients) and will recommence trading only *after* a release, with the probability of trade in LUV stock significantly higher during the ten-minute interval subsequent to a news arrival. This is consistent with the market microstructure theory that investors trade on information (Easley and O'Hara, 1992). In contrast, the *after* coefficients for American Airlines and U.S. Airways Group are overwhelmingly insignificant. This implies the intensity of trading returns quickly to the pre-announcement levels and suggests that market participants absorb new information almost immediately, as in the multiple informed trader model of Holden and Subrahmanyam (1992). Alternatively, Green (2004) argues that lower trading intensity following information flow indicates that uninformed (liquidity) traders are patient with their orders.

Table 2.10 shows that it is more informative to analyse the impact of individual company announcements, as opposed to studying the aggregated effect of all news concurrently, regardless of their different informational content.[7] In contrast to the aggregated results discussed earlier, we observe that at least six out of ten news releases have a significant effect on the frequency of trading in stocks. Unscheduled airline security releases and announcements that are directly related to past or future earnings, such as traffic reports or favourable analysts' reports, have the largest impact on the conditional probability of trade. On average, the news dummy coefficients are positive for all companies, implying that there is a significant decline in the market activity prior and consequent to a company news release.

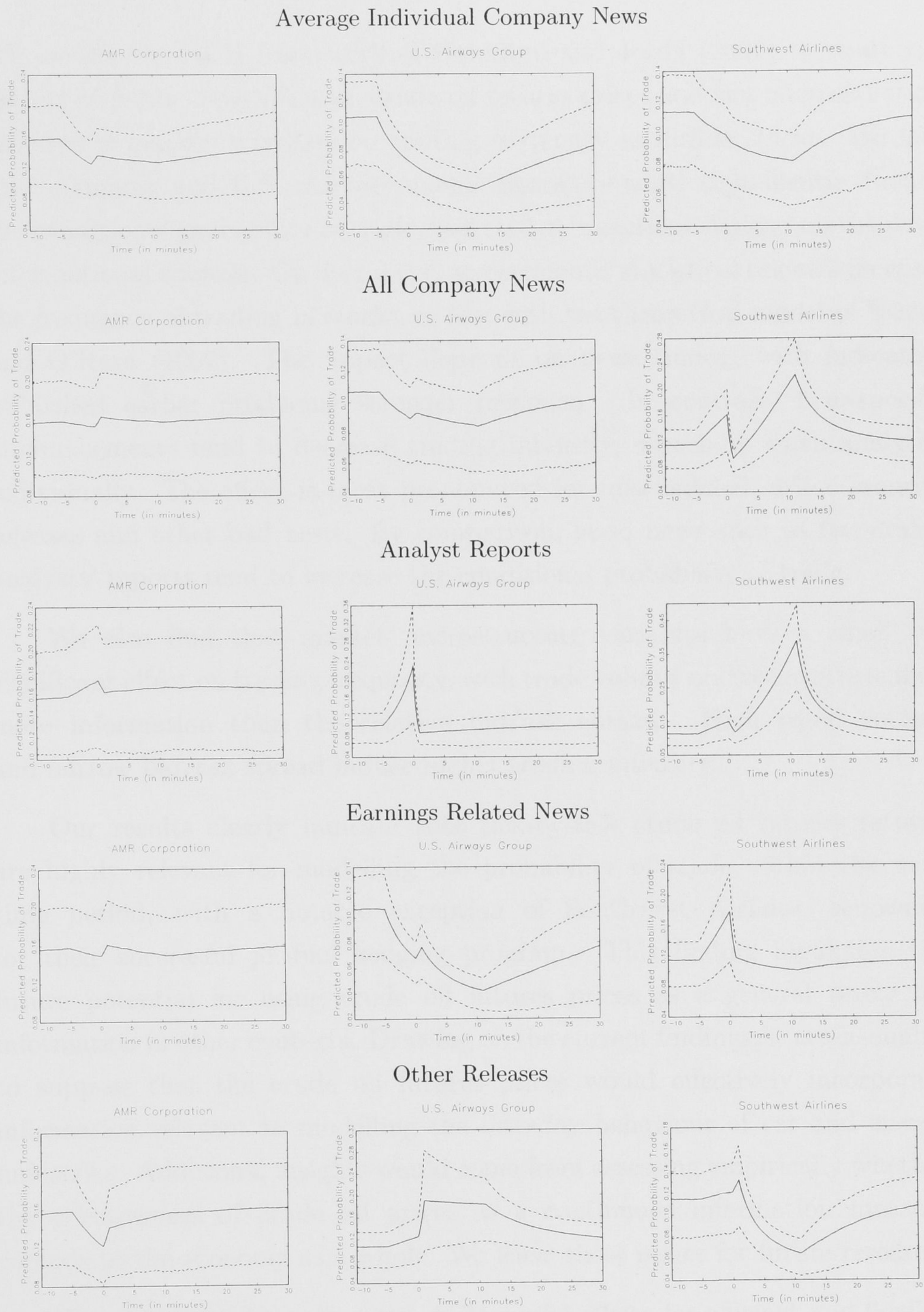
Figure 2.8 illustrates the above finding. The top panel, which contains plots of the average median behaviour of trading frequency in the presence of individual firm-specific announcements, is most striking. Hazard rates monotonically decrease within the window of five minutes before to ten–twelve minutes after the release, and remain below the pre-announcement levels for more than thirty minutes. In particular, trades in LCC and LUV stocks are unlikely to occur, with the conditional probabilities of trade as low as 0.0507 and 0.0817, respectively, compared with the average probabilities

[7]There are two instances, when AMR specific and macroeconomic news were released concurrently. To check the robustness of our individual company announcement results, we re-estimate the models with an indicator for all macro news, with the observation window of 1+10 minutes. Throughout, this dummy is statistically significant in models of AMR and LCC hazard rates (the coefficients are -0.0009 and -0.0020, respectively, which confirms our finding that macroeconomic releases increase the probability of trade), but our results remain unchanged.

of 0.0955 and 0.1035. This contrasts with the second panel, which contains plots of median response of hazard rates to aggregated company releases. In this case, there is no response of AMR hazard rates, while the probability of trade in LUV stock significantly increases before and after releases. Analysis of the next three panels reveals that the conditional probability of trade in LUV stock increases during analyst reports and earnings related news, but falls during other announcements. The hazard lines for American Airline are almost flat, again indicating that averaging announcements is suboptimal. For U.S. Airways, we observe a sharp increase in frequency of trading shortly after analyst reports and after other news, but a decrease after earnings announcements.

Why do market participants react differently to the same type of announcements? Kim and Verrecchia (1997) argue that since investors vary in skill at interpreting public information, news releases actually increase information asymmetry. Moreover, while the impact of individual firm-specific announcements is not systematic, there seems to be some evidence that good news increases the conditional probability of trade, whereas bad news induces a slow-down in trading activity. Examples of announcements that reduced the intensity of trading include AMR and LCC related security releases following the alleged terror plot at London airport (10 August) and then two jet diversions because of security concerns (25 August). On the other hand, favourable traffic reports, new routes announcements and affirmative analyst reports all tend to raise hazard rates. This is illustrated by a Standard & Poor's (S&P) Equity Research Services report on 10 August. The 10.05 news on this date contained information about American Airlines being specifically targeted by the terrorists. After a series of subsequent releases and updates, S&P Equity Research lowered its fundamental outlook on the airline sub-industry at 15.26. As a result, frequency of trading in AMR and LCC stocks declined even further. Interestingly, this report strongly affected the probability of trade in Southwest Airline stock, too, although in a positive way. The attempted terrorist attacks of the day and high oil prices were the main reasons for the downgrade. Yet LUV is a domestic carrier and it is well known for its successful jet-fuel hedging strategy. Hence, it is not surprising that investors were keen to trade more frequently in LUV stocks following the S&P analysis.

Figure 2.8: Trading Frequency Responses to Firm-Specific Announcements



Notes: The solid lines represent the median behaviour of trading frequency in the presence of company releases, and the dashed lines represent the 95% confidence bounds. Both estimates are obtained using Monte Carlo simulations based on parameter estimates reported in Tables 2.9 – 2.10. The x-axis denotes time in minutes, with the announcement time fixed at 0. The sample consists of 967,500 one-second observations based on NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ database and NYSE.

2.6 Conclusions

We modify the ACH framework of Hamilton and Jordà (2002) to study the impact of public news releases, crude oil futures prices and key microstructure features of market activities on trading frequency in airline stocks. We find that company and U.S. macroeconomic announcements significantly change the conditional probability of trade, but traders' reactions depend on the news informational content. On average, macroeconomic statistical releases increase the frequency of trading in stocks, in line with the theoretical model of Easley and O'Hara (1992). The impact depends on news timing, with indicators published earlier producing stronger response. In contrast, firm-specific announcements tend to decrease trading intensity, especially when analysed individually. The effect is most pronounced for unscheduled airline security releases and other bad news. By comparison, good news such as favourable analysts' reports tend to increase the conditional probability of trade.

We also find that market microstructure variables have a small yet significant effect on trading frequency, with trade volume and returns revealing more information than the relative bid/ask spread. High trade volume and narrow bid/ask spread induce higher trading intensity.

Our results clearly indicate that tick-by-tick crude oil futures returns are highly relevant for modelling the probability of trade within the next time period, with a notable exception of Southwest Airlines, renowned for their successful jet-fuel hedging program. This finding highlights the future potential for using crude oil futures prices as a general proxy for information in other contexts. Drawing on the current findings, it is reasonable to suppose that the crude oil futures prices would effectively incorporate information relevant to modelling the intraday behaviour of car and energy industries. Additional insights would come from assessing empirically whether the effectiveness of crude oil prices as a continuous information measure extends to the economy as a whole. We leave these issues for future research.

We provide evidence that the ACH model allows for efficient and flexible modelling of the conditional probability of trade in the next time interval. However, another interesting direction for future research would be to extend the model so that it can account for nonlinearities and asymmetry in the response of stock prices to information (asymmetries in adjusting to good/bad news are reported for example by Gosnell et al., 1996, in their study of dividend announcements). A smooth transition ACH framework could be developed for this purpose, in line with the research work of Teräsvirta and Anderson (1992), Anderson and Vahid (1998, 2001) and Anderson et al. (1999). Further extensions of the model could also include semiparametric and nonparametric estimation techniques, as in the closely related framework of Gerhard and Hautsch (2001).

Chapter 3

High-Frequency Probability Forecasting using Autoregressive Conditional Hazard Models

3.1 Introduction

This chapter uses high-frequency stock market data to investigate the forecasting properties of the autoregressive conditional hazard (ACH) model of Hamilton and Jordà (2002). This analysis is performed in the context of modelling trading frequency and predicting the conditional probability of a trade occurring within the next time interval. While several papers have successfully employed the ACH framework to model in-sample conditional probabilities (see Demiralp and Jordà, 2001; Hamilton and Jordà, 2002; Andersen et al., 2007b; and the analysis in chapter 2), this is the first study to examine the out-of-sample forecasting performance of the ACH model. The evaluation is conducted on time series of trades, computed from transaction and quote data of NYSE listed airline stocks. The financial tick-by-tick dataset entails a very large out-of-sample environment, so that the out-of-sample predictive accuracy of the ACH model can be statistically assessed.

Forecasts of binary indicators of an event defined on the basis of a continuous variable—as opposed to forecasts of the conditional means of the continuous variable itself—are increasingly common in empirical economics and finance. For example, forecasts of economic recessions are of more interest to policymakers and market participants than simple point forecasts of expected output growth, particularly when limited information about the forecast uncertainty is provided (Clements and Harvey, 2006). Other economic and financial forecasts that are often issued as probabilities are the probability of exceeding the target inflation rate, the probability of a financial crisis, or the default probability for corporate bonds (Diebold and Lopez, 1996; and Clements and Harvey, 2006).

In this chapter we apply the ACH methodology to produce probability forecasts of a trade in airline stocks occurring within the next short time interval. Five probability forecasts are generated using different amounts of information and different model specifications. These include three newly-developed, more flexible ACH specifications. The motivation for introducing the extensions is threefold: firstly, to account for information available since the last observed trade. Secondly, to guarantee the non-negativity of the expected conditional durations in the presence of exogenous covariates that significantly shorten the expected time between trades, such as news releases. Thirdly, to accommodate nonlinear effects of shorter and longer trade durations on the expected conditional durations and trade intensity (Dufour and Engle, 2000a). Two of the extensions, namely logarithmic and exponential ACH, are counterparts to the autoregressive conditional duration (ACD) models reported in the empirical literature as most appropriate for modelling trade durations (see Hautsch, 2004).

The forecasting performance of the models is assessed using out-of-sample probability forecast evaluation techniques such as quadratic and logarithmic probability scores, forecast encompassing tests, and probability forecasts combinations. We show that the ACH model is a valuable forecasting tool, with all five ACH specifications strongly outperforming two benchmark forecasts. The most accurate forecasts are generated by the new ACH model that includes a measure of the length of time passed since the last observed trade (i.e. a "no-trade duration," as explained below). In contrast, the logarithmic and exponential ACH models fit poorly, and are outperformed by the basic ACH model. Forecast encompassing tests clearly indicate the potential for further accuracy gains. In particular, Kamstra-Kennedy forecast combinations (Kamstra and Kennedy, 1998) based on the ACH model with the no-trade duration variable improve on the best individual forecast, in line with the literature for mean forecast combinations.

The remainder of the chapter is organized as follows: Section 3.2 describes the theoretical properties of the standard ACH specification and introduces several model extensions. Section 3.3 reviews methods for evaluating and combining probability forecasts. Data and its statistical properties are described in Section 3.4. The results of the application of the ACH methodology to probability forecasting are reported and discussed in Section 3.5. Section 3.6 concludes the chapter.

3.2 Forecasting Conditional Probabilities

In this section, we discuss the most important features of the ACH model in the context of modelling and predicting high-frequency conditional probabilities. We also introduce three new model specifications that allow for more flexible modelling of the data, namely ACH model with no-trade durations, logarithmic ACH and exponential ACH. The ACH model with no-trade durations is design to account for more of the data dynamics than the baseline ACH model, while the logarithmic and exponential extensions are counterparts to the ACD models reported in the empirical literature as most appropriate for modelling trade durations (see Hautsch, 2004). All extensions are estimated as the (1,1) models to facilitate the comparison of the new specifications with the baseline ACH(1,1) model.

3.2.1 Autoregressive Conditional Hazard Model

We model the conditional probability of a trade occurring by the end of the next time interval within the ACH framework of Hamilton and Jordà (2002). Let $x_t = 1$ if a trade occurs within $(t-1, t]$ and $x_t = 0$ otherwise. The conditional probability of $x_t = 1$, called the *hazard rate* h_t, is then defined as

$$h_t \equiv \Pr\left(x_t = 1 \mid \Omega_{t-1}\right), \tag{3.1}$$

where Ω_{t-1} denotes the information set known at time $t-1$. Hamilton and Jordà (2002) utilise the properties of the geometric distribution to show that the hazard rate is inversely related to the expected length of time until the next trade, ψ_t, since

$$\psi_t = \sum_{j=1}^{\infty} j\left(1-h_t\right)^{j-1} h_t = \frac{1}{h_t}, \tag{3.2}$$

and thus

$$h_t = \frac{1}{\psi_t}. \tag{3.3}$$

As in the ACD framework of Engle and Russell (1998), the expected length of time until the next trade, or the *expected conditional duration*, is a function of past observed and expected durations.

Consider a stochastic process of trade arrival times, $\{t_1, t_2, \ldots, t_n\}$, with the nth trade arriving at the end of time t_n and $t_1 < t_2 < \cdots < t_n$. A *duration* u_n is defined as the length of time (the interval) between the $(n-1)$th and the nth trade arrival times, that is, $u_n = t_n - t_{n-1}$. The ACD(p, q) model predicts that the conditional expectation of the duration u_n is a weighted average of p past durations and q past expectations that are known at time t_{n-1}. That is, given past observations $u_{n-1}, u_{n-2}, \ldots$, the ACD(p, q) model implies that

$$\mathbb{E}[u_n | u_{n-1}, u_{n-2}, \ldots] \equiv \psi_n = \omega + \sum_{j=1}^{p} \alpha_j u_{n-j} + \sum_{j=1}^{q} \beta_j \psi_{n-j}, \tag{3.4}$$

where $\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$. The expected duration ψ_n can be expressed in terms of calendar time t with a help of an associated *counting process* $N(t)$, which is the cumulative number of trades that have occurred by the end of time t. Therefore, $N(t) = N(t-1)$ if a trade does not occur in the interval $(t-1, t]$ and $N(t) = N(t-1) + 1$ if it does, such that

$$\psi_{N(t)} = \omega + \sum_{j=1}^{p} \alpha_j u_{N(t)-j} + \sum_{j=1}^{q} \beta_j \psi_{N(t)-j}, \tag{3.5}$$

where the expectation $\psi_{N(t)}$ is formulated at time t_{n-1}.

As with the generalized autoregressive conditional heteroscedastic (GARCH) and ACD models, equation (3.5) can be easily generalised to account for linear effects of covariates $\mathbf{z}_{t-1}$ known at time $t - 1$, such as public news releases, crude oil prices and market microstructure variables (see chapter 2). However, the exogenous covariates can change even if a trade does not occur. This implies that the expected conditional duration ψ_t changes by the end of every (calendar) time interval, through

$$\psi_t = \psi_{N(t)} + \delta \mathbf{z}_{t-1}. \tag{3.6}$$

where δ denotes a vector of parameters.

Feasible estimation of the parameters of interest requires some model modification, because at the time $t - 1$ the value of $N(t)$ is unknown, as are the values of $u_{N(t)-j}$ or $\psi_{N(t)-j}$. To overcome this problem, we specify the hazard rate as

$$h_t = \frac{1}{\psi_t}, \tag{3.7}$$

$$\psi_t = \omega + \sum_{j=0}^{p-1} \alpha_{(j+1)} u_{N(t-1)-j} + \sum_{j=1}^{q} \beta_j \psi_{t-j} + \delta \mathbf{z}_{t-1}. \tag{3.8}$$

Then the parameters in (3.8) can then be estimated using maximum likelihood techniques, with the conditional log-likelihood specified as

$$\mathcal{L}(\theta) = \sum_{t=1}^{T} \left\{ x_t \log(h_t) + (1 - x_t) \log(1 - h_t) \right\} \tag{3.9}$$

where $\theta = (\omega, \alpha', \beta', \delta')'$.

We use two model specifications to forecast hazard rates: a baseline ACH(1,1) and an ACH(2,1) with market microstructure variables and crude oil futures returns. The univariate ACH(1,1) model is specified as

$$h_t = \frac{1}{\psi_t} \tag{3.10}$$

$$\psi_t = \omega + \alpha_1 u_{N(t-1)} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t \in \tau(j)}, \tag{3.11}$$

where $I_{t \in \tau(j)}$ denotes time indicators that account for intradaily seasonality in the data and j = (9:45–10:59), (11:00–11:59), (12:00–13:59) and (14:00–14:59). Chapter 2 shows that the ACH(1,1) adequately accounts for most of the dynamic dependencies in the data. However, across different lag structure specifications, the ACH(2,1) model is found to provide the best data fit, as judged by the likelihood and Bayesian Information Criterion (BIC) statistics and in-sample forecast performance. Model fit is further improved when lagged market microstructure effects and trading spillovers from the crude oil futures market are accounted for. Therefore, specification of the conditional duration process is given by

$$h_t = \frac{1}{\psi_t}, \tag{3.12}$$

$$\begin{aligned} \psi_t &= \omega + \alpha_1 u_{N(t-1)} + \alpha_2 u_{N(t-1)-1} + \beta_1 \psi_{t-1} \\ &+ \sum_{j=1}^{4} \gamma_j I_{t \in \tau(j)} + \delta \mathbf{z}_{t-1}, \end{aligned} \tag{3.13}$$

where $\mathbf{z}_{t-1}$ denotes a vector of market microstructure covariates that include the relative bid/ask spread, the logarithmic trade volume and return (see Dacarogna et al., 2001, for definitions and stylized facts), and returns of the current front-month NYMEX light sweet crude oil futures contract.

3.2.2 ACH Model with a "No-trade Duration" Variable

The first new ACH specification that we introduce in this chapter is based on an innovation time component that is unpredictable *ex-ante*. Let ℓ_t be a step function defined as

$$\ell_t = \begin{cases} 0 & \text{if trade occurs within the interval } (t-1, t], \\ \ell_{t-1} + 1 & \text{otherwise.} \end{cases} \tag{3.14}$$

This variable measures how much time has passed since the last observed trade. Put differently, ℓ_t is the time interval between the latest observed trade $t_{N(t)}$ and current time t, or a *no-trade duration*. For the standard ACH specification, the contribution of this duration to the conditioning information set is limited, due to the long memory in expected conditional hazards (β_1 close to one, see Sections 2.5.1 and 3.5.1). Thus our motivation is to develop an ACH model that is more careful in moving from the trade time $N(t)$ to the real time t. The proposed correction not only accounts for the information available at time of the previous trade, but also includes more of the recent information. We denote this improved ACH specification as ℓ-ACH(1,1), to highlight the inclusion of a measure of the *length of time since the last observed trade*.

Including the latest observed no-trade duration ℓ_{t-1} in the information set Ω_{t-1} changes the conditional duration process (3.11) into the following equation

$$\psi_t = \omega + \alpha_1 u_{N(t-1)} + \beta_1 \psi_{t-1} + \delta_l \ell_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t \in \tau(j)}, \tag{3.15}$$

which can be also written in terms of the innovations as

$$\begin{aligned} \psi_t = {} & \omega + \alpha_1 \left(u_{N(t-1)} - \psi_{t-1} \right) + \beta^* \psi_{t-1} + \delta_l \left(\ell_{t-1} - \psi_{t-1} \right) \\ & + \sum_{j=1}^{4} \gamma_j I_{t \in \tau(j)}, \end{aligned} \tag{3.16}$$

where $\beta^* = \alpha_1 + \beta_1 + \delta_l$, and $\left(u_{N(t-1)} - \psi_{t-1}\right)$ and $(\ell_{t-1} - \psi_{t-1})$ can be viewed as innovations. Denoting the scaled sum of both innovation as v_t (i.e. $v_t = \alpha_1 \left(u_{N(t-1)} - \psi_{t-1}\right) + \delta_l (\ell_{t-1} - \psi_{t-1})$) yields

$$\psi_t = \omega + \beta^* \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)} + v_t.$$

i.e. on average the process can be viewed as an AR(1) in the conditional expected durations.

3.2.3 Logarithmic ACH Model

The logarithmic ACD model of Bauwens and Giot (2000) implies a nonlinear relationship between the expected and observed durations, as the autoregressive equation is based on the logarithm of the conditional expected durations. This specification is more flexible than the standard ACD model; no parameter restrictions are required to ensure the non-negativity of the left-hand side durations in the presence of covariates that significantly shorten the expected time between trades. Bauwens and Giot (2000) propose two versions of the logarithmic ACD; one resembling the Log-GARCH model of Geweke (1986), and another based on the Exponential-GARCH model of Nelson (1991). The first version, denoted as Log-ACD$_1$, assumes that the logarithm of the conditional duration is a function of its past lagged values and the logarithm of the lagged trade durations:

$$\psi_n = \exp\left[\omega + \sum_{j=1}^{p} \alpha_j \ln u_{n-j} + \sum_{j=1}^{q} \beta_j \ln \psi_{n-j}\right]. \tag{3.17}$$

The second version replaces lagged trade durations with lagged *excess durations* (also called *standardised durations*), defined as

$$\varepsilon_{n-j} = \frac{u_{n-j}}{\psi_{n-j}}. \tag{3.18}$$

The Log-ACD$_2$ is then specified as

$$\psi_n = \exp\left[\omega + \sum_{j=1}^{p} \alpha_j \varepsilon_{n-j} + \sum_{j=1}^{q} \beta_j \ln \psi_{n-j}\right]. \tag{3.19}$$

Bauwens and Giot (2000) report that both models account for the dynamic dependencies in the data as well as the basic ACD, with the Log-ACD$_2$ model providing the best data fit. Bauwens et al. (2005a), who compare several ACD extensions via density forecasts, offer similar conclusions. Interestingly, the basic ACD and Log-ACD are found to account for dynamics in financial durations at least as successfully as more complex and difficult to estimate alternatives, such as the Threshold ACD (see Zhang et al., 2001), the Stochastic Volatility Duration model (Ghysels et al., 2004), and the Stochastic Conditional Duration model (Bauwens and Veredas, 1999). This result prompts Bauwens et al. (2005a) to conclude that the modelling framework should be kept "simple but not too simple." Pacurar (2008) reports that most empirical studies use the basic ACD and Log-ACD models, with the Log-ACD$_2$ version favoured due to better data fit.

Given the better empirical performance of the Log-ACD$_2$ model, we specify the logarithmic ACH (LACH) as its counterpart. That is, the LACH(p, q) is defined as

$$h_t = \frac{1}{\psi_t}, \tag{3.20}$$

$$\psi_t = \exp\left[\omega + \sum_{j=0}^{p-1} \alpha_{(j+1)} \left(\frac{u_{N(t-1)-j}}{\psi_{t-j-1}}\right) + \sum_{j=1}^{q} \beta_j \ln \psi_{t-j}\right]. \tag{3.21}$$

The LACH(1,1), equation (3.21) is simply

$$\psi_t = \exp\left[\omega + \alpha \left(\frac{u_{N(t-1)}}{\psi_{t-1}}\right) + \beta \ln \psi_{t-1}\right]. \tag{3.22}$$

3.2.4 Exponential ACH Models

Dufour and Engle (2000a) suggest the Log-ACD specification is likely to over-predict the conditional expected duration after very short trade durations due to the asymptotic convergence to minus infinity of the logarithm of zero. Zero durations occur often due to multiple trades arriving during the same second. Their impact may be ignored by merging simultaneous trades (see for example Engle and Russell, 1998, and Engle and Patton, 2004). Alternatively, Dufour and Engle (2000a) propose a piece-wise linear parameterization of the ACD model that results in shorter and longer durations having different, though still linear, effects. The model is called the EXponential ACD (ExACD) model, since it is also based on the Exponential-GARCH (Nelson, 1991), and is specified as

$$\psi_n = \exp\left[\omega + \sum_{j=1}^{p}\left[\alpha_j\varepsilon_{n-j} + \alpha_j^*\left|\varepsilon_{n-j} - 1\right|\right] + \sum_{j=1}^{q}\beta_j \ln\psi_{n-j}\right]. \tag{3.23}$$

Therefore, the impact on the conditional expected duration varies, depending on the observed durations being shorter or longer than its conditional expectation (i.e. $\varepsilon_{n-j} < 1$ determines a slope equal to $\alpha_j - \alpha_j^*$, whereas $\varepsilon_{n-j} > 1$ implies a slope equal to $\alpha_j + \alpha_j^*$). Fernandes and Grammig (2006), who assess the empirical performance of a family of ACD models that encompasses the ExACD, provide evidence that modelling financial durations requires the additional flexibility of the asymmetric logarithmic specification. Similar results are reported by Hautsch (2004).

Analogously, we specify the exponential ACH (EACH) model as

$$h_t = \frac{1}{\psi_t}, \tag{3.24}$$

$$\begin{aligned}\psi_t = \exp&\left[\omega + \sum_{j=0}^{p-1}\left[\alpha_{(j+1)}\left(\frac{u_{N(t-1)-j}}{\psi_{t-j-1}}\right) + \alpha_{(j+1)}^*\left|\frac{u_{N(t-1)-j}}{\psi_{t-j-1}} - 1\right|\right]\right. \\ &\left. + \sum_{j=1}^{q}\beta_j \ln\psi_{t-j}\right].\end{aligned} \tag{3.25}$$

In case of the EACH(1,1), equation (3.25) simplifies to

$$\psi_t = \exp\left[\omega + \alpha\left(\frac{u_{N(t-1)}}{\psi_{t-1}}\right) + \alpha^*\left|\frac{u_{N(t-1)}}{\psi_{t-1}} - 1\right| + \beta\ln\psi_{t-1}\right]. \tag{3.26}$$

3.3 Evaluating and Combining Probability Forecasts

We use the ACH model to forecast whether a trade will occur during the time interval $(t+k-1, t+k]$, given the information set Ω_t known at present. The conditional probability of $x_{t+k} = 1$ is given by the hazard rate $h_{t+k|t}$, which is a k-step-ahead forecast of x_{t+k}. For a sequence of T probability forecasts and outcomes, $\left\{h_{t+k|t}, x_{t+k|t}\right\}$, $t = 1, \ldots, T$, the accuracy of the probability forecasts is evaluated (or 'scored') using *quadratic probability scores* (QPS, introduced by Brier, 1950), and *logarithmic probability scores* (LPS). If we define the forecast errors as $e_{t+k} = x_{t+k} - h_{t+k|t}$, then the quadratic probability score is defined similarly to the standard mean squared forecast error (MSFE) measure calculated to evaluate point forecasts. That is

$$QPS = \frac{1}{T} \sum_{t=1}^{T} 2 \left(h_{t+k|t} - x_{t+k} \right)^2, \tag{3.27}$$

whereas the logarithmic probability score is calculated as

$$LPS = -\frac{1}{T} \sum_{t=1}^{T} \left[x_{t+k} \ln h_{t+k|t} + (1 - x_{t+k}) \ln \left(1 - h_{t+k|t} \right) \right]. \tag{3.28}$$

Like the MSFE, low QPS and LPS indicate that forecasts are accurate, with zero being the lower bound; the upper bound is two for QPS and infinity for LPS. Also, both scores apply a symmetric penalty to positive and negative prediction errors, and heavily penalise large mistakes (Anderson and Vahid, 2001). Empirical applications that utilise QPS and LPS include Diebold and Rudebusch (1998), Anderson and Vahid (2001), and Clements and Harvey (2007).

Scoring probability forecasts allows us to identify a set of accurate forecasting models. If one forecast does not include all information contained in another forecast(s), then the forecast accuracy can be further increased through a combination of the multiple individual forecasts (see Clemen, 1989 for a comprehensive review of theoretical and empirical literature). Tests of *forecast encompassing* determine whether a combination of competing forecasts produces statistically more accurate predictions than the best individual model of the collection. For point forecasts, these tests are usually based on the MSFE loss function; see Timmermann (2006) and West (2006). For probability forecasts, Clements and Harvey (2006) develop a testing framework based on the quadratic and logarithmic scoring rules, as described below. This framework uses a linear combination of two k-step-ahead forecasts of x_{t+k}, denoted as $h^1_{t+k|t}$ and $h^2_{t+k|t}$. The combined forecast is defined as

$$h^c_{t+k|t} = \lambda_0 + \lambda_1 h^1_{t+k|t} + \lambda_2 h^2_{t+k|t}, \tag{3.29}$$

where $\lambda = \{\lambda_0, \lambda_1, \lambda_2\}$ denotes the combination parameters. In this setting, when imposing a parameter restriction $\lambda_2 = 0$ on equation (3.29) does not result in a statistically larger loss function, forecast $h^1_{t+k|t}$ encompasses forecast $h^2_{t+k|t}$. Conversely, if forecast $h^2_{t+k|t}$ encompasses forecast $h^1_{t+k|t}$, then imposing the restriction $\lambda_1 = 0$ produces a loss function that is significantly smaller than using the combination forecast (Timmermann, 2006). In both cases, the constituent forecasts are unbiased if $\lambda_0 = 0$ (Clements and Harvey, 2006).

The QPS forecast encompassing test is based on the linear probability model:

$$x_{t+k} = \lambda_0 + \lambda_1 h^1_{t+k|t} + \lambda_2 h^2_{t+k|t} + \varepsilon_{t+k}. \tag{3.30}$$

In this setting, the null hypothesis that $h^1_{t+k|t}$ encompasses $h^2_{t+k|t}$ is $\lambda_2 = 0$. Clements and Harvey (2006) show that an encompassing test based on (3.30) is unaffected by parameter estimation uncertainty. This is in contrast to tests based on regressions that impose additional restrictions on the combination parameters, such as $\lambda_1 + \lambda_2 = 1$ (West, 2001) or $\lambda_1 = 1$ (West and McCracken, 1998).

Clements and Harvey (2006) establish that for the k-step-ahead forecasts, the forecast errors ε_{t+k} should be autocorrelated of order no more than $k-1$. In particular, for the 1-step-ahead forecasts that we consider in Section 3.5.2, the forecast errors should be serially uncorrelated. They propose an estimator of the variance-covariance matrix of λ that accounts for $(k-1)$ dependence, based the framework developed by Diebold and Mariano (1995). However, this estimator does not account for the inherent heteroscedasticity in the linear probability model residuals (under the null hypothesis that $\lambda_2 = 0$, the forecast errors ε_{t+k} equal either $\left(1 - \lambda_0 - \lambda_1 h^1_{t+k|t}\right)$ or $\left(-\lambda_0 - \lambda_1 h^1_{t+k|t}\right)$, since x_{t+k} equals either 1 or 0). In consequence, we estimate equation (3.30) using the weighted least squares (WLS) techniques. For the 1-step-ahead forecasts considered, the variance of the forecast errors $Var\left(\varepsilon_{t+1}\right)$ is given by $\left[h^1_{t+1|t}\left(1 - h^1_{t+1|t}\right)\right]$ under the null hypothesis of forecast $h^1_{t+1|t}$ encompassing forecast $h^2_{t+1|t}$. We use the reciprocal of the squared root of $Var\left(\varepsilon_{t+1}\right)$ as weights for the WLS estimation of equation (3.30). Then the big-sample test statistic becomes the standard t-statistic that has a standard normal distribution under the null hypothesis.

It should be noted that while the WLS estimation yields efficient estimators of the combination parameters for 1-step-ahead forecasts, this technique alone is inappropriate for longer forecast horizons. Further, Clements and Harvey (2006) argue that non-model-based forecasts may exhibit dependence structure of order more than $k-1$. A simple solution in these situations is to employ the Newey-West autocorrelation-consistent estimator in the WLS regression, with the Newey-West lag truncation set equal to the integer part of $\left(4\left(T/100\right)^{\frac{2}{9}}\right)$.

The second type of forecast encompassing tests for probability forecasts employs the logarithmic probability score and is based on the maximum likelihood estimation (MLE) of the log-likelihood function given by

$$\mathcal{L}(\lambda) = -\frac{1}{T}LPS = \sum_{t=1}^{T}\left[x_{t+k}\ln h^c_{t+k|t} + (1-x_{t+k})\ln\left(1-h^c_{t+k|t}\right)\right], \quad (3.31)$$

where $h^c_{t+k|t}$ is defined using (3.29). This test requires an autocorrelation correction even for $k = 1$. Clements and Harvey (2006) propose an autocorrelation-consistent variance covariance estimator of λ_2 based on the outer product-of-the-gradient (OPG) estimator of the covariance matrix of $\hat{\lambda}$. Let g denote the $(T \times 3)$ gradient matrix of (3.6) given by

$$g_t = \begin{pmatrix} \frac{\partial \mathcal{L}_t}{\partial \lambda_0} & \frac{\partial \mathcal{L}_t}{\partial \lambda_1} & \frac{\partial \mathcal{L}_t}{\partial \lambda_2} \end{pmatrix},$$

where

$$\begin{aligned}
\frac{\partial \mathcal{L}_t}{\partial \lambda_0} &= \left(\frac{x_{t+k}}{h^c_{t+k|t}}\right) - \left(\frac{1-x_{t+k}}{1-h^c_{t+k|t}}\right), \\
\frac{\partial \mathcal{L}_t}{\partial \lambda_1} &= h^1_{t+k|t}\left(\frac{x_{t+k}}{h^c_{t+k|t}} - \frac{1-x_{t+k}}{1-h^c_{t+k|t}}\right), \\
\frac{\partial \mathcal{L}_t}{\partial \lambda_2} &= h^2_{t+k|t}\left(\frac{x_{t+k}}{h^c_{t+k|t}} - \frac{1-x_{t+k}}{1-h^c_{t+k|t}}\right),
\end{aligned}$$

and denote g_t evaluated at $\hat{\lambda}$ as $\hat{g}_t$. The OPG estimator of the covariance matrix of $\hat{\lambda}$ is given by $\hat{V}^G = \left(\sum_{t=1}^{T}\hat{g}'_t\hat{g}_t\right)^{-1}$, whereas the autocorrelation-consistent variance estimator is calculated as

$$\hat{V}_E = \hat{V}^G\left(\sum_{t=1}^{T}\hat{g}'_t\hat{g}_t + \sum_{\tau=1}^{L}\sum_{t=\tau+1}^{T}\left(1-\frac{\tau}{1+L}\right)\left(\hat{g}'_t\hat{g}_{t-\tau} + \hat{g}'_{t-\tau}\hat{g}_t\right)\right)\hat{V}^G, \quad (3.32)$$

with the Newey-West lag truncation set to be the integer part of $\left(4\left(T/100\right)^{\frac{2}{9}}\right)$. Under the null hypothesis of no encompassing, the test statistic $t = \hat{\lambda}_2 / \sqrt{\left(\hat{V}_E\right)_{3,3}}$ has a standard normal distribution asymptotically. It is worth noting that for the LPS test, the OPG estimator of the covariance matrix of $\hat{\lambda}$ is asymptotically equivalent to the quasi-maximum likelihood estimator (QMLE, White, 1982). The implication is twofold: first, the QMLE estimator is routinely included in most econometrics software packages, which simplifies the computational aspects of the test. Second, the QMLE estimator is robust to model misspecifications, that may arise for example due to heteroscedasticity in the forecast errors (Clements and Harvey, 2006).

The forecast encompassing tests facilitate a pairwise evaluation of competing predictions and identification of (two) forecasts that can be efficiently combined. However, combining probability forecasts requires extra care in ensuring that the combined forecast is still a variable bounded between zero and one (Clements and Harvey, 2007). Combination of log odds ratios, introduced by Kamstra and Kennedy (1998), guarantees that $h^c_{t+k|t} \in [0, 1]$. This method combines two forecasts, $h^1_{t+k|t}$ and $h^2_{t+k|t}$, in the following way:

$$h^c_{t+k|t} = \frac{\exp\left[\lambda_0 + \lambda_1 \ln\left(\frac{h^1_{t+k|t}}{1-h^1_{t+k|t}}\right) + \lambda_2 \ln\left(\frac{h^2_{t+k|t}}{1-h^2_{t+k|t}}\right)\right]}{1 + \exp\left[\lambda_0 + \lambda_1 \ln\left(\frac{h^1_{t+k|t}}{1-h^1_{t+k|t}}\right) + \lambda_2 \ln\left(\frac{h^2_{t+k|t}}{1-h^2_{t+k|t}}\right)\right]}. \tag{3.33}$$

The combination weights λ are the maximum likelihood estimates from a logit regression of x_{t+k} on a constant, $\ln\left(\frac{h^1_{t+k|t}}{1-h^1_{t+k|t}}\right)$ and $\ln\left(\frac{h^2_{t+k|t}}{1-h^2_{t+k|t}}\right)$. Clements and Harvey (2007) report that the Kamstra-Kennedy combination forecasts perform more accurately than other combination methods that do not guarantee the combined forecast to be a probability, such as linear and logarithmic opinion pools.

3.4 Data and Summary Statistics

The empirical analysis is based on the tick-by-tick transaction and order data for three large airlines listed on the New York Stock Exchange (NYSE), namely AMR Corporation (AMR), Southwest Airlines (LUV) and U.S. Airways Group (LCC). The airline data is supplemented by the New York Mercantile Exchange (NYMEX) intraday current month light sweet crude oil futures price data. The use of crude oil futures data in the model serves as a continuous information measure and a proxy for a set of oil related surprises, as discussed in chapter 2. The raw airline data comes from the NYSE Trade and Quote (TAQ) database, supplied by Wharton Research Data Services, whereas the crude oil futures data comes from the Comprehensive Quotes and Graphics (CQG), an official NYMEX data vendor. The sample period for all assets begins on 1 August 2006 and ends on 10 October 2006. Information based on the NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006 is used for the initial forecasting model estimation. The out-of-sample period is defined from 1 to 10 October 2006 and consists of 157,500 one-second observations.

The considered airline stocks are traded very frequently, with trade durations averaging between 7 and 11 seconds. We thus model and forecast the probability of a trade occurring within one-second intervals. An average transaction has a volume of 519 to 1,144 shares and a bid-ask spread of 1 to 4 cents. All variables exhibit positive, highly significant and very persistent dynamic dependencies, that are characteristic for long memory processes. Further, both trade durations and frequency reveal very strong diurnality. The probability of trade exhibits a U-shaped pattern over the course of the day, that is also characteristic for volatility, trade volumes and bid/ask spreads. On average, trades are about twice as likely to occur during the opening auction and immediately prior to the market's close than during lunch-time. Conversely, the time-of-day seasonality in trade durations exhibits an inverse U-shape, as first documented by Engle and Russell (1998). A more detailed discussion of the dataset, its summary statistics and the methods employed in preparing it for the analysis are available in Section 2.4.1.

3.5 Empirical Results

3.5.1 In-Sample ACH Estimates

In Tables 3.1–3.3 we provide the in-sample estimation results and diagnostics for all airlines stocks in August and September 2006. We report results for the ACH(1,1), ACH(2,1) with market microstructure variables and crude oil futures returns, ℓ-ACH(1,1) with no-trade durations, Logarithmic ACH(1,1), and Exponential ACH(1,1). For each stock-model combination, we report quasi-maximum likelihood estimates (with robust standard errors), the Bayesian Information Criterion (BIC), and the in-sample probability scores. To complement this information, Figures 3.1–3.3 show diagnostic plots for the estimated ACH models. Figure 3.1 plots the average observed and fitted hazard rates to indicate which model provides the best in-sample fit. Figures 3.2 and 3.3 plots the autocorrelation and partial autocorrelation functions of the standardized binary residuals defined as

$$\hat{\varepsilon}_t = \frac{x_t - \hat{h}_t}{\sqrt{\hat{h}_t \cdot \left(1 - \hat{h}_t\right)}}. \tag{3.34}$$

Examining the dynamic dependencies in the standardized binary residuals is an important part of goodness-of-fit evaluation, since significant autocorrelation in the estimated residuals signals a misspecified model.

The main features of the in-sample results are as follows: First, significant autoregressive effects are the key characteristic of the basic ACH models for all stocks. The β coefficients are close to one, indicating a strong persistence in the dynamics of the duration process that are reported in the ACD literature (see Hautsch, 2004, for a review). The inclusion of the covariates only marginally changes the estimates of the β coefficients. In contrast, controlling for the no-trade durations and changing the functional form of the expected conditional duration process drastically lowers the β coefficients and clearly changes the way in which the model captures persistence. These changes are potentially important for forecasting. The innovation parameters α are conspicuously low for all five models, indicating infrequent updating of the expected conditional hazards. The α^* parameter in the EACH model is, however, statistically significant, indicating that the response to innovations is asymmetric.

Second, the results strongly indicate that the ℓ-ACH(1,1) model offers uniformly the best in-sample results in terms of the highest total log-likelihood, the best BIC criterion, and the smallest QPS and LPS scores. This model also has better specification diagnostics than other models. In particular, this model is more successful in accounting for the autocorrelation in the data than the other models. The first-order autocorrelation coefficient for the ℓ-ACH(1,1) standardized binary residuals is on average seven times smaller than for any other residuals (see Figure 3.1 and note that the scale for the ℓ-ACH(1,1) model is much smaller than for the other graphs). Additionally, the model provides a good approximation to trade frequency dynamics (see Figures 3.2 and 3.3), though somewhat less accurately than the ACH(2,1) model, which has a richer set of explanatory variables.

In line with our expectations, the no-trade duration has the largest effect on the frequency of trading. Each 10 seconds without a trade

Table 3.1: Parameter Estimates of ACH Models for AMR Corporation

	ACH(1,1)	ACH(2,1)	ℓ-ACH(1,1)	LACH	EACH
ω	**0.0008**	**0.0186**	**3.8580**	**0.6548**	**1.5502**
	[0.0002]	[0.0019]	[0.0515]	[0.0332]	[0.0957]
α_1	**0.0011**	**0.0009**	**0.1165**	**0.0569**	**0.1908**
	[0.0001]	[0.0001]	[0.0028]	[0.0027]	[0.0115]
α_2		**0.0010**			
		[0.0001]			
β_1	**0.9985**	**0.9973**	**-0.1396**	**0.6118**	**0.1169**
	[0.0001]	[0.0002]	[0.0062]	[0.0192]	[0.0541]
α_1^*					**-0.1589**
					[0.0108]
ℓ_{t-1}			**0.4734**		
			[0.0051]		
oil_{t-1}		**-0.0007**			
		[0.0002]			
$return_{t-1}$		**0.0023**			
		[0.0012]			
$volume_{t-1}$		**-0.0030**			
		[0.0003]			
$spread_{t-1}$		0.0001			
		[0.0001]			
lnL	-379,362.9	-378,707.3	-372,995.7	-383,083.8	-382,713.2
BIC	758,822.3	757,579.9	746,101.6	766,264.1	765,536.8
QPS	0.2329	0.2325	0.2295	0.2349	0.2347
LPS	0.3921	0.3914	0.3855	0.3960	0.3956

Notes: We model the conditional probability of trade (h_t) in AMR Corporation stock as $h_t = 1/\psi_t$, with the conditional expected duration ψ_t specified as

$$\begin{aligned}
\text{ACH(1,1)}: \psi_t &= \omega + \alpha_1 u_{N(t-1)} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}, \\
\text{ACH(2,1)}: \psi_t &= \omega + \alpha_1 u_{N(t-1)} + \alpha_2 u_{N(t-1)-1} + \beta_1 \psi_{t-1} + \delta \mathbf{z}_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}, \\
\ell\text{-ACH(1,1)}: \psi_t &= \omega + \alpha_1 u_{N(t-1)} + \beta_1 \psi_{t-1} + \delta_l \ell_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}, \\
\text{LACH}: \psi_t &= \exp\left[\omega + \alpha\left(\frac{u_{N(t-1)}}{\psi_{t-1}}\right) + \beta \ln \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}\right], \\
\text{EACH}: \psi_t &= \exp\left[\omega + \alpha\left(\frac{u_{N(t-1)}}{\psi_{t-1}}\right) + \alpha^* \left|\frac{u_{N(t-1)}}{\psi_{t-1}} - 1\right| + \beta \ln \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}\right],
\end{aligned}$$

where ℓ_{t-1} denotes the time interval between the latest observed trade $t_{N(t-1)}$ and time $t-1$, and $\mathbf{z}_{t-1}$ denotes a vector of exogenous covariates: *oil* (the current month NYMEX light sweet crude oil futures returns), *return* (the return constructed from the share price series), *volume* (the logarithm of the number of shares traded), and *spread* (the relative bid/ask spread). All covariates have been scaled to have unit variances. Parameter estimates of time indicators $I_{t\in\tau(j)}$ are not reported in the table, although they were included in the estimated models. Coefficient estimates provided in **bold** are significant at the 5% level (robust standard errors). The sample consists of 967,500 one-second observations based on NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ and CQG databases.

Table 3.2: Parameter Estimates of ACH Models for U.S. Airways Group

	ACH(1,1)	ACH(2,1)	ℓ-ACH(1,1)	LACH	EACH
ω	**0.0029**	**0.0442**	**4.6075**	**0.6851**	**0.9791**
	[0.0003]	[0.0049]	[0.0782]	[0.0360]	[0.0451]
α_1	**0.0011**	**0.0010**	**0.0937**	**0.0578**	**0.1212**
	[0.0001]	[0.0001]	[0.0031]	[0.0029]	[0.0053]
α_2		**0.0010**			
		[0.0001]			
β_1	**0.9984**	**0.9968**	**-0.0854**	**0.6629**	**0.5369**
	[0.0001]	[0.0003]	[0.0062]	[0.0174]	[0.0210]
α_1^*					**-0.0938**
					[0.0053]
ℓ_{t-1}			**0.6115**		
			[0.0063]		
oil_{t-1}		**-0.0017**			
		[0.0003]			
$return_{t-1}$		**0.0124**			
		[0.0024]			
$volume_{t-1}$		**-0.0061**			
		[0.0006]			
$spread_{t-1}$		**0.0028**			
		[0.0004]			
lnL	-299,134.6	-298,157.2	-288,859.1	-302,110.2	-301,825.3
BIC	598,365.7	596,479.8	577,828.5	604,316.9	603,760.9
QPS	0.1706	0.1702	0.1667	0.1718	0.1717
LPS	0.3092	0.3082	0.2986	0.3123	0.3120

Notes: We model the conditional probability of trade (h_t) in U.S. Airways Group stock as $h_t = 1/\psi_t$, with the conditional expected duration ψ_t specified as

$$
\begin{aligned}
\text{ACH(1,1)}: \psi_t &= \omega + \alpha_1 u_{N(t-1)} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}, \\
\text{ACH(2,1)}: \psi_t &= \omega + \alpha_1 u_{N(t-1)} + \alpha_2 u_{N(t-1)-1} + \beta_1 \psi_{t-1} + \delta \mathbf{z}_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}, \\
\ell\text{-ACH(1,1)}: \psi_t &= \omega + \alpha_1 u_{N(t-1)} + \beta_1 \psi_{t-1} + \delta_l \ell_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}, \\
\text{LACH}: \psi_t &= \exp\left[\omega + \alpha\left(\frac{u_{N(t-1)}}{\psi_{t-1}}\right) + \beta \ln \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}\right], \\
\text{EACH}: \psi_t &= \exp\left[\omega + \alpha\left(\frac{u_{N(t-1)}}{\psi_{t-1}}\right) + \alpha^*\left|\frac{u_{N(t-1)}}{\psi_{t-1}} - 1\right| + \beta \ln \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}\right],
\end{aligned}
$$

where ℓ_{t-1} denotes the time interval between the latest observed trade $t_{N(t-1)}$ and time $t-1$, and $\mathbf{z}_{t-1}$ denotes a vector of exogenous covariates: *oil* (the current month NYMEX light sweet crude oil futures returns), *return* (the return constructed from the share price series), *volume* (the logarithm of the number of shares traded), and *spread* (the relative bid/ask spread). All covariates have been scaled to have unit variances. Parameter estimates of time indicators $I_{t\in\tau(j)}$ are not reported in the table, although they were included in the estimated models. Coefficient estimates provided in **bold** are significant at the 5% level (robust standard errors). The sample consists of 967,500 one-second observations based on NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ and CQG databases.

Table 3.3: Parameter Estimates of ACH Models for Southwest Airlines

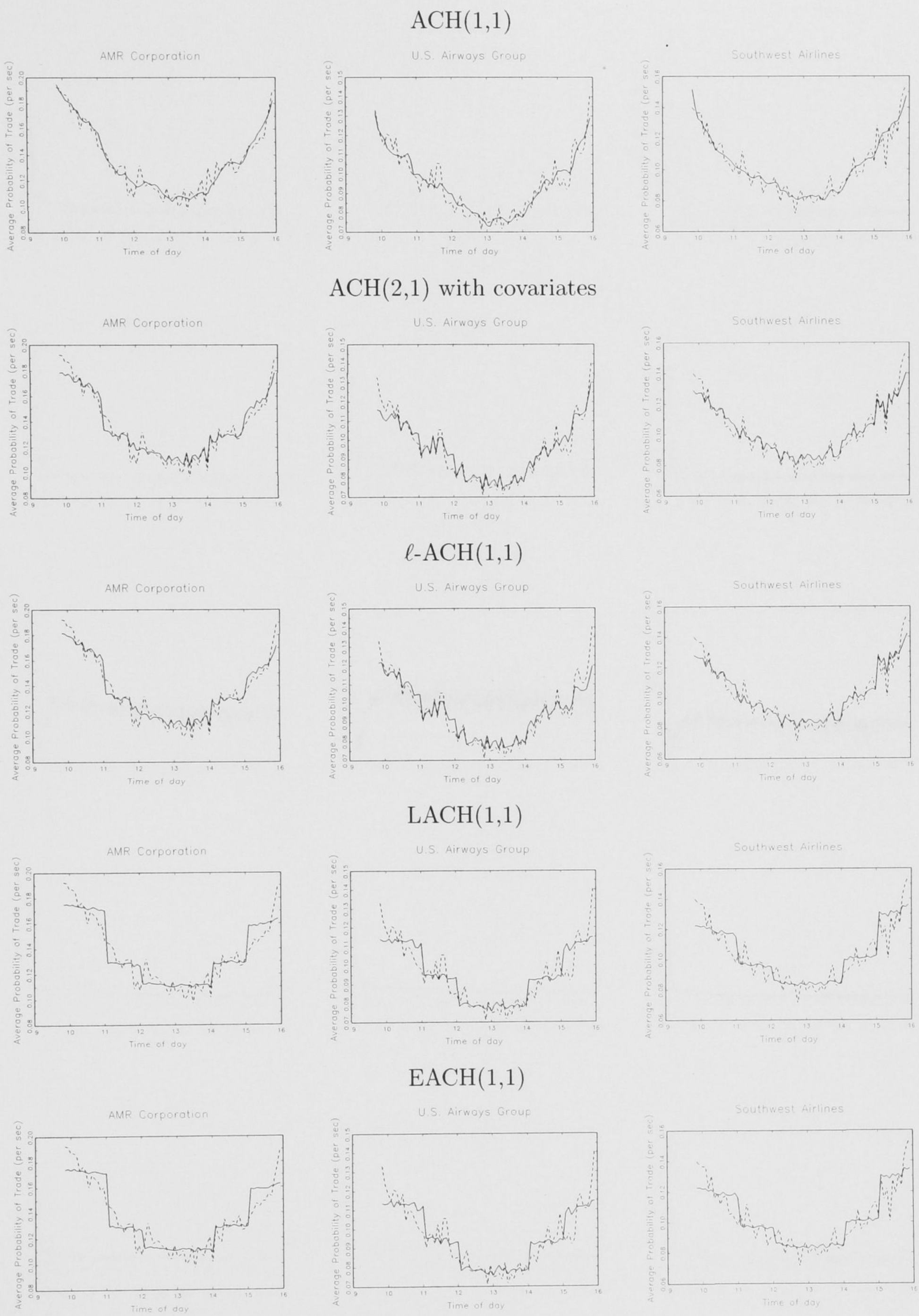
	ACH(1,1)	ACH(2,1)	ℓ-ACH(1,1)	LACH	EACH
ω	**0.0043**	**0.0433**	**4.5512**	**0.7055**	**1.0186**
	[0.0008]	[0.0092]	[0.0572]	[0.1481]	[0.0501]
α_1	**0.0011**	**0.0013**	**0.1379**	**0.0778**	**0.1448**
	[0.0001]	[0.0002]	[0.0014]	[0.0149]	[0.0076]
α_2		**0.0011**			
		[0.0002]			
β_1	**0.9981**	**0.9953**	**-0.1648**	**0.6142**	**0.4704**
	[0.0002]	[0.0009]	[0.0039]	[0.0799]	[0.0248]
α_1^*					**-0.1156**
					[0.0079]
ℓ_{t-1}			**0.4970**		
			[0.0062]		
oil_{t-1}		0.0001			
		[0.0004]			
$return_{t-1}$		**-0.0160**			
		[0.0071]			
$volume_{t-1}$		**-0.0069**			
		[0.0013]			
$spread_{t-1}$		**0.0030**			
		[0.0006]			
lnL	-317,801.7	-317,386.1	-311,979.5	-318,700.1	-318,329.9
BIC	635,699.9	634,937.5	624,069.3	637,496.7	636,770.1
QPS	0.1840	0.1838	0.1813	0.1844	0.1842
LPS	0.3285	0.3280	0.3225	0.3294	0.3290

Notes: We model the conditional probability of trade (h_t) in Southwest Airlines stock as $h_t = 1/\psi_t$, with the conditional expected duration ψ_t specified as

$$
\begin{aligned}
\text{ACH(1,1)}: \psi_t &= \omega + \alpha_1 u_{N(t-1)} + \beta_1 \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}, \\
\text{ACH(2,1)}: \psi_t &= \omega + \alpha_1 u_{N(t-1)} + \alpha_2 u_{N(t-1)-1} + \beta_1 \psi_{t-1} + \delta \mathbf{z}_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}, \\
\ell\text{-ACH(1,1)}: \psi_t &= \omega + \alpha_1 u_{N(t-1)} + \beta_1 \psi_{t-1} + \delta_l \ell_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}, \\
\text{LACH}: \psi_t &= \exp\left[\omega + \alpha\left(\frac{u_{N(t-1)}}{\psi_{t-1}}\right) + \beta \ln \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}\right], \\
\text{EACH}: \psi_t &= \exp\left[\omega + \alpha\left(\frac{u_{N(t-1)}}{\psi_{t-1}}\right) + \alpha^* \left|\frac{u_{N(t-1)}}{\psi_{t-1}} - 1\right| + \beta \ln \psi_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t\in\tau(j)}\right],
\end{aligned}
$$

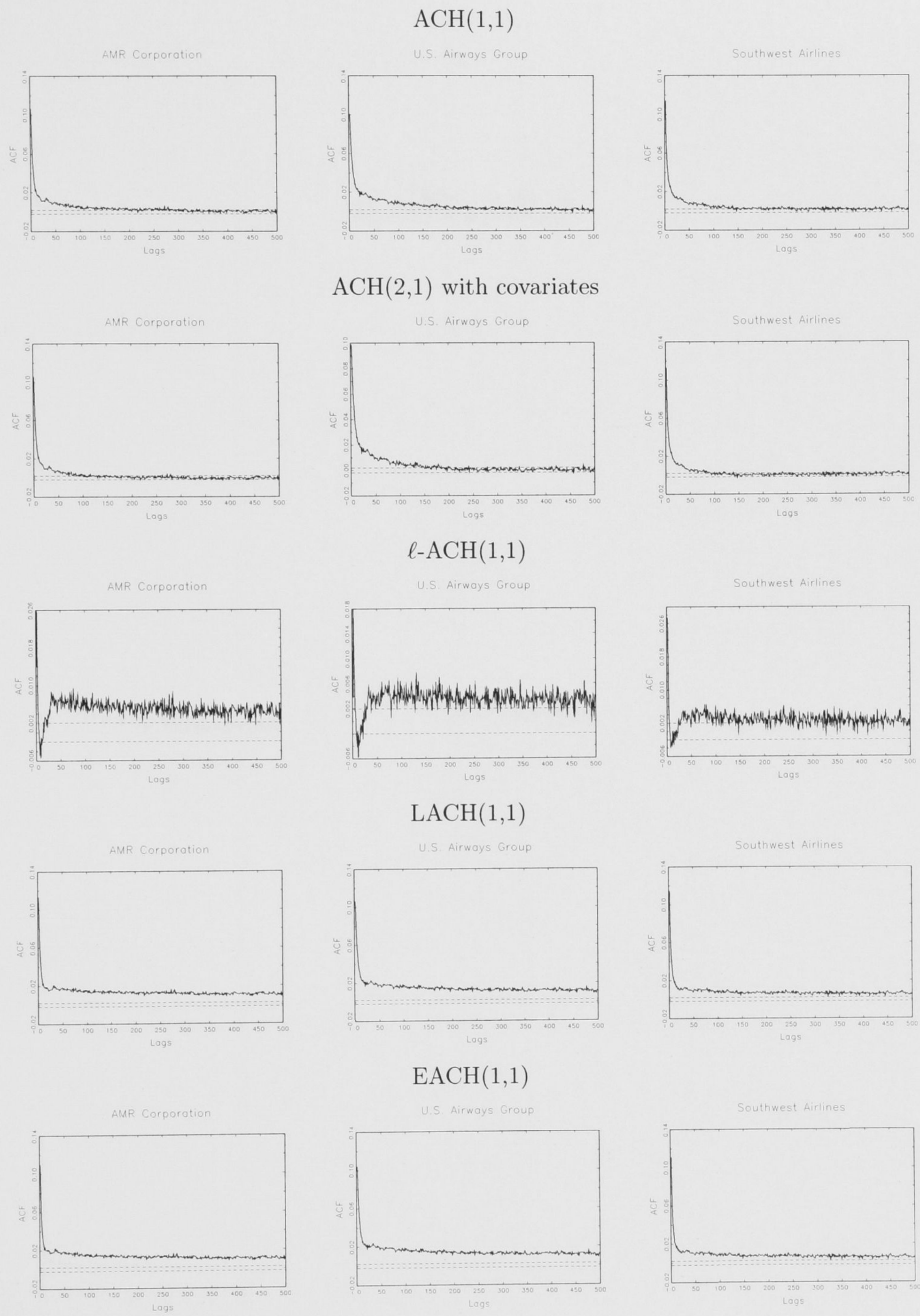
where ℓ_{t-1} denotes the time interval between the latest observed trade $t_{N(t-1)}$ and time $t-1$, and $\mathbf{z}_{t-1}$ denotes a vector of exogenous covariates: *oil* (the current month NYMEX light sweet crude oil futures returns), *return* (the return constructed from the share price series), *volume* (the logarithm of the number of shares traded), and *spread* (the relative bid/ask spread). All covariates have been scaled to have unit variances. Parameter estimates of time indicators $I_{t\in\tau(j)}$ are not reported in the table, although they were included in the estimated models. Coefficient estimates provided in **bold** are significant at the 5% level (robust standard errors). The sample consists of 967,500 one-second observations based on NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ and CQG databases.

Figure 3.1: Model Diagnostics for ACH Models: Intraday Pattern of Actual and Fitted Trade Frequency



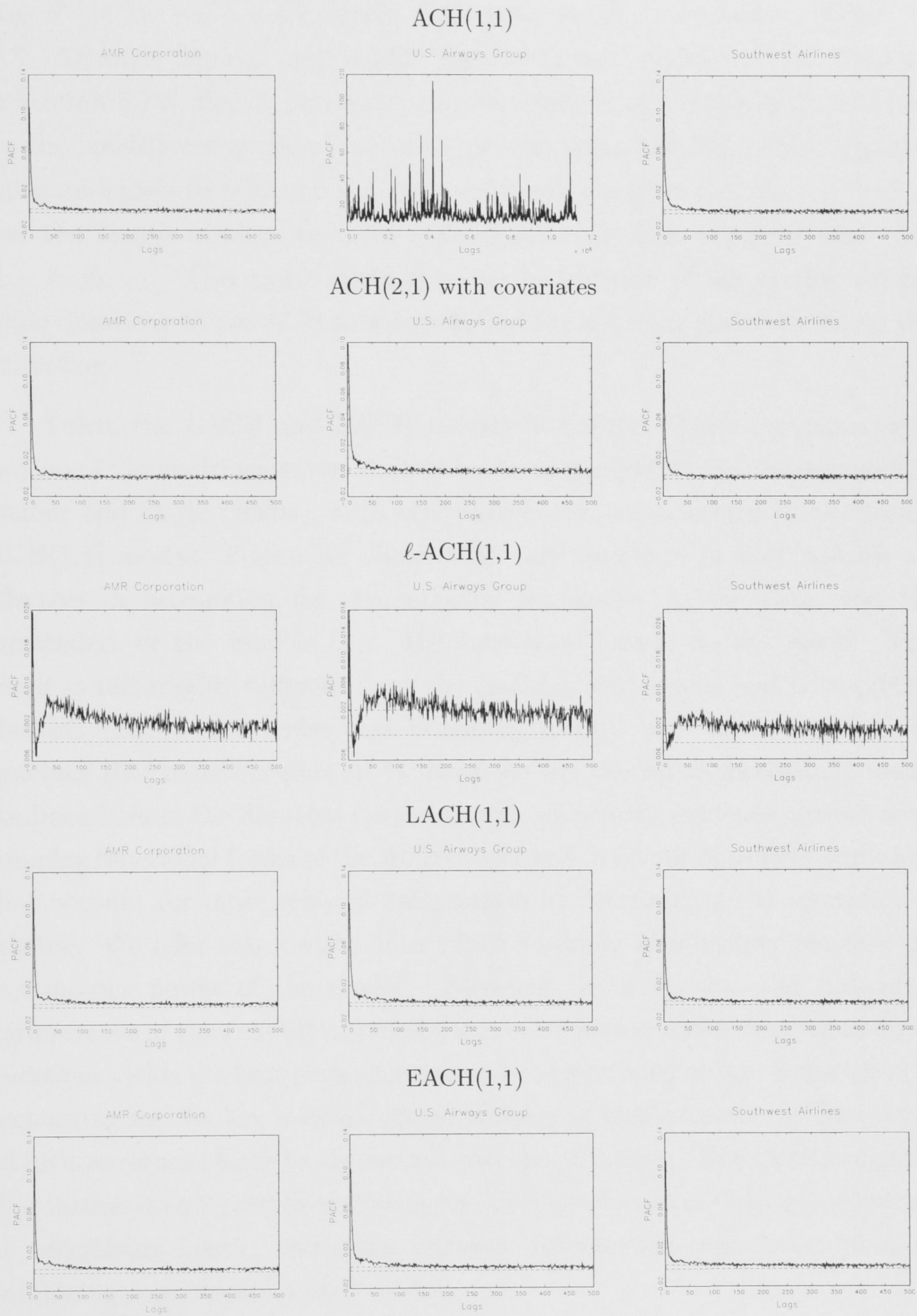
Notes: The relevant parameter estimates are reported in Tables 3.1–3.3. The solid lines represent the fitted average intraday patterns of trade frequency. The dashed lines represent the observed intraday patterns of trade frequency. The averages are based on five-minute intervals of trading activity. The time between trades is measured in seconds and the time of the day is measured in hours since midnight. The sample consists of 967,500 one-second observations based on NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. Data source: TAQ and CQG database.

Figure 3.2: Model Diagnostics for ACH Models: Autocorrelation Functions of Standardized Binary Residuals



Notes: The relevant parameter estimates are reported in Tables 3.1–3.3. The solid lines represent the ACF for the first 500 lags of standardized binary residuals. The dashed lines represent 95% confidence bounds. The sample consists of 967,500 one-second observations based on NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. Data source: TAQ and CQG database.

Figure 3.3: Model Diagnostics for ACH Models: Partial Autocorrelation Functions of Standardized Binary Residuals



Notes: The relevant parameter estimates are reported in Tables 3.1–3.3. The solid lines represent the ACF for the first 500 lags of standardized binary residuals. The dashed lines represent 95% confidence bounds. The sample consists of 967,500 one-second observations based on NYSE trades that occurred between 9.45 and 16.00 in August and September 2006. Data source: TAQ and CQG database.

lengthen the expected conditional duration by 4.73 (AMR Corporation) to 6.11 (U.S. Airways Group) seconds. The sum of the non-intercept coefficients (i.e. $\beta^* = \alpha_1 + \beta_1 + \delta_l$) equals 0.4503 for AMR Corporation, 0.7906 for U.S. Airways Group, and 0.4701 for Southwest Airlines. As discussed in Section 3.2.1, the β^* parameter can be interpreted as an AR(1) coefficient for the conditional expected duration process when the last-period expected duration equals to both the last observed trade duration (i.e. $u_{N(t-1)} = \psi_{t-1}$) and the length of time that has passed since the last observed trade (i.e. $\ell_{t-1} = \psi_{t-1}$). This result highlights the importance of accounting for no-trade durations in the ACH framework, and the accuracy gains offered by this correction.

Third, the LACH and EACH models fit poorly. While the exponential version of the model generates slightly better in-sample results, as suggested by Dufour and Engle (2000a), both new models are outperformed by the simple ACH(1,1) model. Figure 3.1 shows that time dummies in both models are effective in accounting for the intraday seasonality in the data, but the remainders of the models (i.e. the functional forms) do not work. This result is remarkably different from the findings of Bauwens and Giot (2000), Hautsch (2004), Fernandes and Grammig (2006), and Gunn (2007), who conclude that more complex ACD structures are needed to successfully model nonlinearities in the duration data. Instead, we provide evidence against more complex functional forms of the ACH model and in favour of simpler equations that account for more relevant information in determining the frequency of trading. We offer two insights into which variables significantly increase the explanatory power of the model. Foremost, from the superior individual performance of the ℓ-ACH(1,1) model it is evident that controlling for no-trade durations yields the best performing models, as discussed above. Subsequently, accounting for the key microstructure features of market activities and crude oil futures returns leads to the second best specifications. This clearly suggests that further investigations of alternative ACH specifications should concentrate on identifying larger, and more relevant, information sets rather than on developing more sophisticated models.

3.5.2 Forecasting Probabilities with ACH Models

We use the five ACH models reported in Tables 3.1–3.3 to forecast the 1-step-ahead conditional probability of trade ($h_{t+1|t}$), given the information set Ω_t

Table 3.4: Out-of-Sample Forecast Evaluation

	spline	ACH(1,1)	ACH(2,1)	ℓ-ACH(1,1)	LACH	EACH
			Quadratic Probability Score			
AMR	0.9963	0.9901	0.9876	0.9718	0.9942	0.9934
LCC	0.9991	0.9905	0.9895	0.9710	0.9966	0.9963
LUV	0.9965	0.9947	0.9939	0.9755	0.9948	0.9939
			Logarithmic Probability Score			
AMR	0.9960	0.9886	0.9860	0.9681	0.9932	0.9925
LCC	0.9987	0.9859	0.9844	0.9573	0.9941	0.9936
LUV	0.9948	0.9919	0.9909	0.9674	0.9919	0.9903

Notes: We forecast the 1-step-ahead conditional probability of trade ($h_{t+1|t}$) in stocks of AMR Corporation (AMR), U.S. Airways Group (LCC) and Southwest Airlines (LUV), given the information set Ω_t known at present. The forecasts are based on (i) the deterministic intraday patterns in the conditional probability of trade, estimated using using cubic splines with half-hourly knots, and (ii) the ACH models defined in Tables 3.1–3.3. Information based on the NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006 is used for the initial forecasting model estimation. The quadratic (QPS) and logarithmic (LPS) probability scores are defined as

$$QPS = \frac{1}{T}\sum_{t=1}^{T} 2\left(h_{t+1|t} - x_{t+1}\right)^2,$$

$$LPS = -\frac{1}{T}\sum_{t=1}^{T}\left[x_{t+1}\ln h_{t+1|t} + (1 - x_{t+1})\ln\left(1 - h_{t+1|t}\right)\right].$$

where $x_{t+1} = 1$ is a trade occurs during time interval $(t, t+1]$, and $x_{t+1} = 0$ otherwise. Both scores are relative to the benchmark naive forecasts where the conditional probabilities of trade are equal to their in-sample averages. The forecasting windows consist of 157,500 one-second observations based on the NYSE and NYMEX trades that occurred between 9.45 and 16.00 during the out-of-sample period from 01 to 10 October 2006.
Data source: TAQ and CQG databases.

known at present. The forecasts are constructed using the trade and crude oil futures data updated every second. However, due to a high computational cost of updating the parameter estimates, each 1-step ahead forecast is generated using the same in-sample parameter estimates, as reported in Tables 3.1–3.3. We also construct a naive benchmark forecast where the conditional probabilities of trade are equal to their in-sample averages. Furthermore, we use a second benchmark forecast that is based on the deterministic intraday patterns in the in-sample hazard rates. This intraday seasonality is modelled using cubic splines with half-hourly knots. Table 3.4 reports the quadratic and logarithmic probability scores for the spline-based and ACH-based forecast relative to the naive benchmark set to the in-sample average hazard rate. The scores are reported with reference to the naive benchmark to make the comparison of the results easier.

The results in Table 3.4 suggest that the ACH models generate accurate forecasts of the conditional probability of trade dynamics. The predictive performance of all five ACH specifications is better than the performance of the forecasts based on the in-sample averages and the in-sample diurnal patterns. The spline-based forecasts are uniformly more accurate than the naive benchmark. These findings imply that models of the short run dynamics in trading frequency have an excellent out-of-sample predictive power.

More importantly, the in-sample results reported in Section 3.5.1 extend out-of-sample. The QPS and LPS statistics clearly suggest the ℓ-ACH(1,1) model delivers the most accurate probability forecasts. The additional information brought into the ACH(2,1) specification delivers improved forecasts compared to the simple ACH(1,1) model, once again justifying the inclusion of the microstructure covariates and crude oil futures data in the ACH framework. In general, the ACH model in its original version performs better on the dynamics of trade frequencies than the new EACH and LACH specifications. While the EACH model consistently outperforms the LACH model, neither specification offers any improvement with respect to the out-of-sample forecasting accuracy. This finding confirms the point forecast results, surveyed by Mahmoud (1984), that simple forecasting models in general outperform sophisticated methods.

The single exception is Southwest Airlines. For this stock, the EACH-based predictions are more accurate than the ones generated by the ACH(2,1) and ACH(1,1) models. One possible explanation for this result is the very successful "forward buy" jet-fuel futures program that Southwest Airlines are known for (Mandaro, 2008). The implication of this hedging program is that the short-run changes in crude oil futures returns do not affect the probability of trading in the LUV stock (see Section 2.5.1). Consequently, the inclusion of the crude oil futures data in the model increases the forecasting error, thus yielding less accurate forecasts. However, this argument does not explain the poorer performance of the ACH(1,1) model compared to the EACH.

We then use the QPS- and LPS-based forecast encompassing tests to examine the opportunities for further accuracy gains through a combination of two individual probability forecasts. Tables 3.5 and 3.6 report p-values of the null hypothesis that forecast $h^1_{t+1|t}$ (generated by a model given in columns) encompasses forecast $h^2_{t+1|t}$ (generated by a model given in rows). As earlier, the forecasts are based on the five ACH models as well as the deterministic intraday patterns in the in-sample conditional probability of trade, estimated using cubic splines with half-hourly knots. Given the best individual performance of the ℓ-ACH(1,1) model, it is particularly beneficial to assess whether other models generate predictions that contain useful information in

Table 3.5: QPS-based Forecast Encompassing Tests

	spline	ACH(1,1)	ACH(2,1)	ℓ-ACH(1,1)	LACH	EACH
			AMR Corporation			
spline	-	0.0456	0.7833	0.2958	0.0000	0.0000
ACH(1,1)	0.0000	-	0.0000	0.0000	0.0000	0.0000
ACH(2,1)	0.0000	0.0000	-	0.0000	0.0000	0.0000
ℓ-ACH(1,1)	0.0000	0.0000	0.0000	-	0.0000	0.0000
LACH	0.0000	0.0000	0.0000	0.0393	-	0.1769
EACH	0.0000	0.0000	0.0000	0.7746	0.0000	-
			U.S. Airways Group			
spline	-	0.3235	0.0319	0.7400	0.6446	0.1338
ACH(1,1)	0.0000	-	0.0000	0.0000	0.0000	0.0000
ACH(2,1)	0.0000	0.0000	-	0.0000	0.0000	0.0000
ℓ-ACH(1,1)	0.0000	0.0000	0.0000	-	0.0000	0.0000
LACH	0.0000	0.0000	0.0000	0.9228	-	0.6030
EACH	0.0000	0.0000	0.0000	0.1035	0.0000	-
			Southwest Airlines			
spline	-	0.0000	0.0001	0.0207	0.0000	0.0000
ACH(1,1)	0.0000	-	0.0194	0.0002	0.0000	0.0000
ACH(2,1)	0.0000	0.0000	-	0.0000	0.0000	0.0000
ℓ-ACH(1,1)	0.0000	0.0000	0.0000	-	0.0000	0.0000
LACH	0.0000	0.0000	0.0000	0.0063	-	0.0006
EACH	0.0000	0.0000	0.0000	0.3353	0.0000	-

Notes: We forecast the 1-step-ahead conditional probability of trade ($h_{t+1|t}$) in stocks of AMR Corporation, U.S. Airways Group and Southwest Airlines, given the information set Ω_t known at present. The forecasts are based on (*i*) the deterministic intraday patterns in the conditional probability of trade, estimated using cubic splines with half-hourly knots, and (*ii*) the ACH models defined in Tables 3.1–3.3. Information based on the NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006 is used for the initial forecasting model estimation. The forecasting windows consist of 157,500 one-second observations based on the NYSE and NYMEX trades that occurred between 9.45 and 16.00 during the out-of-sample period from 01 to 10 October 2006. This table reports p-values of the null hypothesis that forecast $h^1_{t+1|t}$ (generated by a model given in columns) encompasses forecast $h^2_{t+1|t}$ (generated by a model given in rows), i.e. $\lambda_2 = 0$. The test is based on the WLS estimation of the linear probability model

$$x_{t+1} \quad = \quad \lambda_0 + \lambda_1 h^1_{t+1|t} + \lambda_2 h^2_{t+1|t} + \varepsilon_{t+1},$$

with weights equal to $w_{t+1} = \left[h^1_{t+1|t}\left(h^1_{t+1|t}\right)\right]^{-1/2}$ under the null hypothesis of forecast $h^1_{t+k|t}$ encompassing forecast $h^2_{t+k|t}$. *Data source*: TAQ and CQG databases.

terms of delivering a statistically-significant reduction in the probability scores when used in combination with the the ℓ-ACH(1,1)-based forecasts.

In general, the forecast encompassing tests suggest the potential for further accuracy gains through forecast combinations. Specifically, the QPS-based tests indicate that only the ℓ-ACH(1,1) model generates forecasts

Table 3.6: LPS-based Forecast Encompassing Tests

	spline	ACH(1,1)	ACH(2,1)	ℓ-ACH(1,1)	LACH	EACH
			AMR Corporation			
spline	-	0.2059	0.7293	0.0107	0.0534	0.0195
ACH(1,1)	0.0000	-	0.0280	0.0000	0.0000	0.0000
ACH(2,1)	0.0000	0.0000	-	0.0000	0.0000	0.0000
ℓ-ACH(1,1)	0.0000	0.0000	0.0000	-	0.0000	0.0000
LACH	0.0000	0.0000	0.0000	0.2917	-	0.7051
EACH	0.0000	0.0000	0.0000	0.0750	0.0000	-
			U.S. Airways Group			
spline	-	0.5898	0.9736	0.0237	0.3722	0.5424
ACH(1,1)	0.0000	-	0.1151	0.0000	0.0000	0.0000
ACH(2,1)	0.0000	0.0000	-	0.0000	0.0000	0.0000
ℓ-ACH(1,1)	0.0000	0.0000	0.0000	-	0.0000	0.0000
LACH	0.0000	0.0000	0.0000	0.0055	-	0.7150
EACH	0.0000	0.0000	0.0000	0.0017	0.0000	-
			Southwest Airlines			
spline	-	0.0078	0.0040	0.0001	0.0005	0.0015
ACH(1,1)	0.0000	-	0.0688	0.0000	0.0000	0.0000
ACH(2,1)	0.0000	0.0000	-	0.0000	0.0000	0.0000
ℓ-ACH(1,1)	0.0000	0.0000	0.0000	-	0.0000	0.0000
LACH	0.0000	0.0000	0.0000	0.0368	-	0.0774
EACH	0.0000	0.0000	0.0000	0.0010	0.0000	-

Notes: We forecast the 1-step-ahead conditional probability of trade ($h_{t+1|t}$) in stocks of AMR Corporation, U.S. Airways Group and Southwest Airlines, given the information set Ω_t known at present. The forecasts are based on (*i*) the deterministic intraday patterns in the conditional probability of trade, estimated using cubic splines with half-hourly knots, and (*ii*) the ACH models defined in Tables 3.1–3.3. Information based on the NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006 is used for the initial forecasting model estimation. The forecasting windows consist of 157,500 one-second observations based on the NYSE and NYMEX trades that occurred between 9.45 and 16.00 during the out-of-sample period from 01 to 10 October 2006. This table reports p-values of the null hypothesis that forecast $h^1_{t+1|t}$ (generated by a model given in columns) encompasses forecast $h^2_{t+1|t}$ (generated by a model given in rows), i.e. $\lambda_2 = 0$. The test is based on the maximum likelihood estimation of the likelihood function given by

$$\mathcal{L}(\lambda) = \sum_{t=1}^{T} \left[x_{t+1} \ln h^c_{t+1|t} + (1 - x_{t+1}) \ln \left(1 - h^c_{t+1|t}\right)\right],$$

where the combined forecast $h^c_{t+k|t}$ is defined as

$$h^c_{t+1|t} = \lambda_0 + \lambda_1 h^1_{t+1|t} + \lambda_2 h^2_{t+1|t}.$$

The test employs the autocorrelation-consistent variance estimator of $\hat{\lambda}$ given by equation (3.32). *Data source*: TAQ and CQG databases.

that systematically encompass some other forecasts; namely the predictions generated by the cubic splines and the augmented ACH models. However, this conclusion is only marginally supported by the LPS-based tests. The null hypothesis that the ℓ-ACH(1,1) predictions convey all the useful information in the other individual forecasts is rejected for all but two stock-model combinations, with the AMR-LACH and the AMR-EACH pairs being the only exceptions.

All five ACH models generate forecasts that often encompass the spline-based predictions. This holds regardless of whether accuracy is assessed by QPS or LPS; for QPS the null is rejected more often. However, the null that the spline-based forecasts encompass any ACH-based forecasts is clearly rejected. This is consistent with the superior in-sample performance of the models that account for the short-run dynamics in the frequency of trading. Further, it provides out-of-sample evidence of adequacy of the set of four time indicators $I_{t\in\tau(j)}$, employed to account for the intradaily seasonality in durations in a parsimonious way. The time dummies provide as satisfactory explanation of the deterministic seasonal patterns as the more complex cubic splines with frequent knots, provided that the data dynamics are modelled at the same time.

Finally, we consider the forecasting accuracy of different forecast combinations. Tables 3.7 and 3.8 report the quadratic and logarithmic probability scores for the forecast combinations obtained through combining forecast $h^1_{t+1|t}$ (generated by a model given in columns) and $h^2_{t+1|t}$ (generated by a model given in rows). The reported scores are calculated relative to the corresponding scores for the ℓ-ACH(1,1)-based forecasts, shown earlier to be the most accurate individual predictions.

From Table 3.8 we see that all individual forecasts combined with the predictions generated by the ℓ-ACH(1,1) model have lower LPS score than the best individual forecasts produced by the ℓ-ACH(1,1) specification. This is consistent with previous findings about point forecasts (see Mahmoud, 1984, for an early review). The LPS evaluations are largely confirmed by the QPS-based evaluations of forecast accuracy (Table 3.7). Forecasting accuracy is improved by combining forecasts from the application of the ℓ-ACH(1,1) model with any other individual forecast for AMR Corporation, the ACH(1,1)- and ACH(2,1)-generated forecasts for U.S. Airways Group, and the predictions produced by the ACH(2,1) model only for Southwest Airlines. For the three

Table 3.7: QPS-based Forecast Combination Evaluation

	spline	ACH(1,1)	ACH(2,1)	ℓ-ACH(1,1)	LACH	EACH
			AMR Corporation			
spline	-	1.0184	1.0161	0.9994	1.0210	1.0202
ACH(1,1)	1.0184	-	1.0160	0.9983	1.0178	1.0172
ACH(2,1)	1.0161	1.0160	-	0.9975	1.0157	1.0151
ℓ-ACH(1,1)	0.9994	0.9983	0.9975	-	0.9994	0.9994
LACH	1.0210	1.0178	1.0157	0.9994	-	1.0203
EACH	1.0202	1.0172	1.0151	0.9994	1.0203	-
			U.S. Airways Group			
spline	-	1.0201	1.0191	1.0001	1.0261	1.0257
ACH(1,1)	1.0201	-	1.0190	0.9978	1.0199	1.0196
ACH(2,1)	1.0191	1.0190	-	0.9975	1.0189	1.0186
ℓ-ACH(1,1)	1.0001	0.9978	0.9975	-	1.0001	1.0001
LACH	1.0261	1.0199	1.0189	1.0001	-	1.0257
EACH	1.0257	1.0196	1.0186	1.0001	1.0257	-
			Southwest Airlines			
spline	-	1.0195	1.0187	1.0003	1.0195	1.0186
ACH(1,1)	1.0195	-	1.0188	1.0001	1.0185	1.0176
ACH(2,1)	1.0187	1.0188	-	0.9999	1.0178	1.0170
ℓ-ACH(1,1)	1.0003	1.0001	0.9999	-	1.0002	1.0002
LACH	1.0195	1.0185	1.0178	1.0002	-	1.0187
EACH	1.0186	1.0176	1.0170	1.0002	1.0187	-

Notes: We forecast the 1-step-ahead conditional probability of trade ($h_{t+1|t}$) in stocks of AMR Corporation, U.S. Airways Group and Southwest Airlines, given the information set Ω_t known at present. The forecasts are based on (i) the deterministic intraday patterns in the conditional probability of trade, estimated using using cubic splines with half-hourly knots, and (ii) the ACH models defined in Tables 3.1–3.3. Information based on the NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006 is used for the initial forecasting model estimation. The forecasting windows consist of 157,500 one-second observations based on the NYSE and NYMEX trades that occurred between 9.45 and 16.00 during the out-of-sample period from 01 to 10 October 2006. This table reports the quadratic probability scores, as defined in Table 3.4, for the combination of forecast $h^1_{t+1|t}$ (obtained from a model given in columns) and $h^2_{t+1|t}$ (obtained from a model given in rows). The forecasts are combined in the following way:

$$h^c_{t+1|t} = \frac{\exp\left[\lambda_0 + \lambda_1 \ln\left(\frac{h^1_{t+1|t}}{1-h^1_{t+1|t}}\right) + \lambda_2 \ln\left(\frac{h^2_{t+1|t}}{1-h^2_{t+1|t}}\right)\right]}{1+\exp\left[\lambda_0 + \lambda_1 \ln\left(\frac{h^1_{t+1|t}}{1-h^1_{t+1|t}}\right) + \lambda_2 \ln\left(\frac{h^2_{t+1|t}}{1-h^2_{t+1|t}}\right)\right]},$$

where the combination weights λ are the maximum likelihood estimates from a logit regression of x_{t+1} on a constant, $\ln\left(\frac{h^1_{t+1|t}}{1-h^1_{t+1|t}}\right)$ and $\ln\left(\frac{h^2_{t+1|t}}{1-h^2_{t+1|t}}\right)$. All scores are relative to the best single model forecasts obtained from the ℓ-ACH(1,1) model. *Data source*: TAQ and CQG databases.

Table 3.8: LPS-based Forecast Combination Evaluation

	spline	ACH(1,1)	ACH(2,1)	ℓ-ACH(1,1)	LACH	EACH
			AMR Corporation			
spline	-	1.0206	1.0181	0.9988	1.0234	1.0225
ACH(1,1)	1.0206	-	1.0180	0.9974	1.0199	1.0191
ACH(2,1)	1.0181	1.0180	-	0.9965	1.0176	1.0169
ℓ-ACH(1,1)	0.9988	0.9974	0.9965	-	0.9988	0.9988
LACH	1.0234	1.0199	1.0176	0.9988	-	1.0226
EACH	1.0225	1.0191	1.0169	0.9988	1.0226	-
			U.S. Airways Group			
spline	-	1.0298	1.0282	0.9993	1.0380	1.0373
ACH(1,1)	1.0298	-	1.0281	0.9960	1.0290	1.0284
ACH(2,1)	1.0282	1.0281	-	0.9955	1.0276	1.0270
ℓ-ACH(1,1)	0.9993	0.9960	0.9955	-	0.9993	0.9992
LACH	1.0380	1.0290	1.0276	0.9993	-	1.0373
EACH	1.0373	1.0284	1.0270	0.9992	1.0373	-
			Southwest Airlines			
spline	-	1.0250	1.0239	0.9998	1.0249	1.0234
ACH(1,1)	1.0250	-	1.0241	0.9991	1.0231	1.0218
ACH(2,1)	1.0239	1.0241	-	0.9988	1.0224	1.0210
ℓ-ACH(1,1)	0.9998	0.9991	0.9988	-	0.9998	0.9996
LACH	1.0249	1.0231	1.0224	0.9998	-	1.0236
EACH	1.0234	1.0218	1.0210	0.9996	1.0236	-

Notes: We forecast the 1-step-ahead conditional probability of trade ($h_{t+1|t}$) in stocks of AMR Corporation, U.S. Airways Group and Southwest Airlines, given the information set Ω_t known at present. The forecasts are based on (i) the deterministic intraday patterns in the conditional probability of trade, estimated using using cubic splines with half-hourly knots, and (ii) the ACH models defined in Tables 3.1–3.3. Information based on the NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006 is used for the initial forecasting model estimation. The forecasting windows consist of 157,500 one-second observations based on the NYSE and NYMEX trades that occurred between 9.45 and 16.00 during the out-of-sample period from 01 to 10 October 2006. This table reports the logarithmic probability scores, as defined in Table 3.4, for the combination of forecast $h^1_{t+1|t}$ (obtained from a model given in columns) and $h^2_{t+1|t}$ (obtained from a model given in rows). The forecasts are combined in the following way:

$$h^c_{t+1|t} = \frac{\exp\left[\lambda_0 + \lambda_1 \ln\left(\frac{h^1_{t+1|t}}{1-h^1_{t+1|t}}\right) + \lambda_2 \ln\left(\frac{h^2_{t+1|t}}{1-h^2_{t+1|t}}\right)\right]}{1+\exp\left[\lambda_0 + \lambda_1 \ln\left(\frac{h^1_{t+1|t}}{1-h^1_{t+1|t}}\right) + \lambda_2 \ln\left(\frac{h^2_{t+1|t}}{1-h^2_{t+1|t}}\right)\right]},$$

where the combination weights λ are the maximum likelihood estimates from a logit regression of x_{t+1} on a constant, $\ln\left(\frac{h^1_{t+1|t}}{1-h^1_{t+1|t}}\right)$ and $\ln\left(\frac{h^2_{t+1|t}}{1-h^2_{t+1|t}}\right)$. All scores are relative to the best single model forecasts obtained from the ℓ-ACH(1,1) model. *Data source*: TAQ and CQG databases.

stocks, the combining procedure of Kamstra and Kennedy (1998) provides the most accurate overall forecast when the ℓ-ACH(1,1)-based forecasts are combined with the ACH(2,1)-based forecasts. This result provides additional evidence that there is clear advantage in accounting for the spillovers from the crude oil futures markets and the information content of the no-trade durations and microstructure covariates.

We further test this proposition by estimating an ℓ-ACH(2,1) model with no-trade durations, crude oil futures returns, market microstructure variables, and time indicators. The in-sample estimation results are provided in Table 3.9. The estimated parameters are similar to these reported in Tables 3.1–3.3 for the individual ℓ-ACH(1,1) and ACH(2,1) with covariates models. The only interesting difference is that the crude oil futures returns become insignificant in the LCC model—though the coefficient itself is of similar magnitude. Remarkably, this model has the best in-sample likelihood, BIC statistics and probability scores across all ACH models considered in this chapter, in line with our out-of-sample conclusions above.

Finally, the in-sample superior performance of models that account for the information content of the no-trade durations, crude oil futures returns, and the microstructure covariates is confirmed out-of-sample. This is evidenced in Table 3.10 that reports the QPS and LPS scores for ℓ-ACH(2,1)-based forecast and for the Kamstra-Kennedy combinations of the two best individual forecasts generated by the ℓ-ACH(1,1) model and the ACH(2,1) model with covariates (as before, the scores are reported relative to the benchmark naive forecasts where the conditional probabilities of trade are equal to their in-sample averages). In all cases the probability scores for both the ℓ-ACH(2,1)-based forecasts and the combination forecasts are a little lower than for any other individual model (as reported in Table 3.4). Interestingly, both QPS and LPS scores indicate that the new ℓ-ACH(2,1) model generates more accurate forecasts than the Kamstra-Kennedy combination for Southwest Airlines, but exactly the opposite is found for U.S. Airways Group. The evidence concerning AMR Corporation is mixed. The QPS suggests that the new model provides more precise forecast, whereas the LPS finds the opposite. This implies that while accounting for the data dynamics and the impact of the relevant covariates offers significant out-of-sample precision gains, obtaining the most accurate results may require estimating a range of forecasting models.

Table 3.9: Parameter Estimates of ℓ-ACH(2,1) Models with Crude Oil Futures Returns, Market Microstructure Variables, and Time Indicators

	AMR	LCC	LUV
ω	**4.9388**	**5.5703**	**7.0919**
	[0.0936]	[0.1473]	[0.1450]
α_1	**0.1222**	**0.0889**	**0.1430**
	[0.0038]	[0.0038]	[0.0039]
α_2	**0.0662**	**0.0440**	**0.0775**
	[0.0026]	[0.0026]	[0.0021]
β_1	**-0.1548**	**-0.0968**	**-0.0794**
	[0.0084]	[0.0083]	[0.0029]
ℓ_{t-1}	**0.4545**	**0.5720**	**0.4348**
	[0.0052]	[0.0064]	[0.0058]
oil_{t-1}	**-0.0438**	-0.0219	-0.0158
	[0.0159]	[0.0222]	[0.0219]
$return_{t-1}$	**0.0187**	**0.0534**	**0.0591**
	[0.0039]	[0.0104]	[0.0070]
$volume_{t-1}$	**-0.3961**	**-0.4039**	**-0.7564**
	[0.0145]	**1.1496**	[0.0130]
$spread_{t-1}$	**0.5611**	[0.0386]	**0.3547**
	[0.0261]	[0.0003]	[0.0263]
lnL	-371,751.1	-287,557.4	-310,486.1
BIC	743,681.3	575,293.9	621,151.5
QPS	0.2288	0.1661	0.1804
LPS	0.3842	0.2972	0.3209

Notes: We model the conditional probability of trade (h_t) in in stocks of AMR Corporation (AMR), U.S. Airways Group (LCC) and Southwest Airlines (LUV) as $h_t = 1/\psi_t$, with the conditional expected duration ψ_t specified as

$$\psi_t = \omega + \alpha_1 u_{N(t-1)} + \alpha_2 u_{N(t-1)-1} + \beta_1 \psi_{t-1} + \delta_l \ell_{t-1} + \delta \mathbf{z}_{t-1} + \sum_{j=1}^{4} \gamma_j I_{t \in \tau(j)},$$

where ℓ_{t-1} denotes the time interval between the latest observed trade $t_{N(t-1)}$ and time $t-1$, and $\mathbf{z}_{t-1}$ denotes a vector of exogenous covariates: *oil* (the current month NYMEX light sweet crude oil futures returns), *return* (the return constructed from the share price series), *volume* (the logarithm of the number of shares traded), and *spread* (the relative bid/ask spread). All covariates have been scaled to have unit variances. Parameter estimates of time indicators $I_{t \in \tau(j)}$ are not reported in the table, although they were included in the estimated models. Coefficient estimates provided in **bold** are significant at the 5% level (robust standard errors). The in-sample period consists of 967,500 one-second observations based on NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006. *Data source*: TAQ and CQG databases.

Table 3.10: Out-of-Sample Forecast Evaluation of ℓ-ACH(2,1) Models with Crude Oil Futures Returns, Market Microstructure Variables, and Time Indicators

	AMR	LCC	LUV
Quadratic Probability Score			
ℓ-ACH(2,1)	0.9691	0.9689	0.9704
combination	0.9693	0.9685	0.9754
Logarithmic Probability Score			
ℓ-ACH(2,1)	0.9655	0.9546	0.9623
combination	0.9647	0.9530	0.9662

Notes: We forecast the 1-step-ahead conditional probability of trade ($h_{t+1|t}$) in stocks of AMR Corporation (AMR), U.S. Airways Group (LCC) and Southwest Airlines (LUV), given the information set Ω_t known at present. The forecasts are based on (i) the ℓ-ACH(2,1) model with no-trade durations, crude oil futures returns, market microstructure variables, and time indicators, reported in Table 3.9, and (ii) the Kamstra-Kennedy combination of forecasts generated by the ACH(2,1) model with the covariates and the ℓ-ACH(1,1) model, as defined in Tables 3.1–3.3. Information based on the NYSE and NYMEX trades that occurred between 9.45 and 16.00 in August and September 2006 is used for the initial forecasting model estimation. The quadratic (QPS) and logarithmic (LPS) probability scores are defined as

$$QPS = \frac{1}{T}\sum_{t=1}^{T} 2\left(h_{t+1|t} - x_{t+1}\right)^2,$$

$$LPS = -\frac{1}{T}\sum_{t=1}^{T}\left[x_{t+1}\ln h_{t+1|t} + (1-x_{t+1})\ln\left(1-h_{t+1|t}\right)\right].$$

where $x_{t+1} = 1$ is a trade occurs during time interval $(t, t+1]$, and $x_{t+1} = 0$ otherwise. Both scores are relative to the benchmark naive forecasts where the conditional probabilities of trade are equal to their in-sample averages. The forecasting windows consist of 157,500 one-second observations based on the NYSE and NYMEX trades that occurred between 9.45 and 16.00 during the out-of-sample period from 01 to 10 October 2006. *Data source*: TAQ and CQG databases.

3.6 Conclusions

As argued in the introduction of this chapter, it is often desirable to forecast the conditional probability of an economic or financial event occurring. In this chapter we demonstrate that the ACH model provides accurate probabilities forecasts, as evaluated using quadratic and logarithmic scoring rules and new tests of probability forecast encompassing developed by Clements and Harvey (2006). An application to U.S. airlines data suggests that pooling information across probability forecasts can deliver accuracy gains. This is consistent with previous findings about point forecasts; in general combined forecasts outperform the constituent forecasts.

Our evaluation of five different ACH specifications demonstrates that using simple ACH models, which make an efficient use of proper information covariates leads to superior probability forecasts. The most accurate individual forecasts are generated by an ACH model that includes a measure of the length of time passed since the last observed trade (i.e. a no-trade duration). In contrast, the application of more complex specifications, which accommodate nonlinearities in the financial data, results in less accurate predictions. Forecasting accuracy is further improved by the means of the Kamstra-Kennedy forecast combinations (Kamstra and Kennedy, 1998) based on the two best performing ACH models that account for the information content of the no-trade durations as well as microstructure variables and spillovers from the crude oil futures markets. This leads us to conclude that future research interested in predicting the probabilities of economic or financial events occurring should concentrate on identifying and testing the most relevant information covariates.

Chapter 4

Macroeconomic Fundamentals, Price Discovery and Volatility Dynamics in Emerging Markets

4.1 Introduction[1]

Insights into how emerging and mature bond markets react to news are valuable for both policy makers disseminating macroeconomic data as well as investors making trading decisions. Policy makers are interested in designing effective policy and communication strategies that are conducive to fundamental price discovery while avoiding unwanted volatility bouts. Understanding market reactions is especially valuable in response to shocks that could spill across borders, putting macroeconomic and financial stability at risk. A good understanding of volatility dynamics and the process of price discovery in emerging markets is also important for market participants' portfolio and risk management. Profitable trading decisions hinge on the knowledge of market reactions to fundamental information, while insights from the volatility response of bond markets help to finetune the order flow and manage risks.

Systematic evidence on the microdynamics of emerging markets' response to macroeconomic releases is scant. Robitaille and Roush (2006) find that

[1]This chapter was mostly written during my internship in the IMF's Research Department, as a joint work with Jochen Andritzky, Andy Jobst, and Natalia Tamirisa. For helpful comments the authors thank Heather Anderson, Tim Bollerslev, Stijn Claessens, Francis Diebold, Raymond Liu, Tom Smith, Sirimon Treepongkaruna, and Farshid Vahid, and participants at the Time-Varying Correlation and Volatility Symposium in Sydney and 21st Australasian Conference in Banking and Finance in Sydney. The authors also gratefully acknowledge discussions with Geoffrey Bannister on a related paper, and thank Gavin Asdorian and David Velasquez-Romero for excellent research assistance.

macroeconomic announcements have significant effects on the mean returns of Brazilian external bonds. However, this study does not account for return dynamics, which risks biasing its conclusions. Wongswan (2006) examines high-frequency data for the Korean and Thai stock markets and finds that both global and local releases affect intraday volatility. In contrast to the scarcity of studies using high-frequency data for emerging markets, there is a sizable literature based on daily data that explores responses to news in both emerging and developed financial markets. A recent study by Andritzky et al. (2007), for example, finds that news has a stronger impact on volatility than on returns in emerging bond markets and that responses to macroeconomic announcements are weaker in times of crisis than in calm periods. The low frequency of the data, however, prevents one from drawing strong inferences about the real-time response to news.

In this chapter, we analyse high-frequency price discovery and volatility dynamics in emerging bond markets and examine the role of macroeconomic fundamentals in asset valuation and trading activity. We model ten-minute returns and volatility using intraday data on the largest issues of emerging external bonds (Brazilian, Mexican, Russian, and Turkish) for the period from October 2006 to February 2008. The empirical setting is based on a two-stage model proposed by Andersen and Bollerslev (1997a) and used extensively in the studies of mature markets by, among others, Andersen et al. (2003).[2] We modify the model specification to fit the unique volatility patterns in emerging markets, particularly the multiplicative rather than additive relationship between the deterministic and stochastic components of volatility. We compare the findings with those in the literature on mature markets and also use data on a U.S. treasury note to analyse more systematically how mature and emerging markets react to news.

How would prices and volatility of emerging assets be expected to react to macroeconomic news? In line with the literature on mature markets, local data releases are expected to have a direct effect on prices and volatility. News from systemically and regionally important economies should also have a strong impact on prices and volatility—such news not only directly affects the predominantly international investors of foreign-currency-denominated emerging market bonds, but they also have bearing on perceptions about

[2]For other applications of the two-stage approach, see Andersen et al. (2000); Bollerslev et al. (2000); Dominguez (2006); and Wongswan (2006).

emerging sovereigns' repayment capacity.[3] As for the duration of the adjustment, information absorption may well take longer in emerging markets than in mature markets, given their lower liquidity and greater information asymmetries.

When examining market reaction to news, we distinguish two types of adjustment: *repricing* (the price impact) and *repositioning* (the volatility impact). *Repricing* involves a shift in asset prices as traders discern the implications of public news for the fair value of a bond, in line with the theoretical model of Kim and Verrecchia (1991b). Within this framework, investors form their expectations before the release of news about macroeconomic fundamentals and trade accordingly. Following an announcement, traders revise their beliefs and trade only if there is a surprise component in the news, i.e., the released data differ from market expectations. Good-news surprises cause an increase in prices, whereas bad-news surprises result in a decrease.

The recommencement of trading following an announcement is further reflected in an increase in trading activity, as investors rebalance their portfolios in light of new information to fit their risk preferences (Andersson, 2007). The market microstructure literature posts that this *repositioning* effect stems from information asymmetry between informed and liquidity traders (Admati and Pfleiderer, 1988), and investors' heterogeneity in interpreting public information (Kim and Verrecchia, 1997). In the Admati and Pfleiderer (1988) model, informed traders concentrate their trades during periods of high market activity, such as around public announcement times, to ensure that their informed trading has little effect on prices and that they can benefit from the liquidity externalities generated by other traders. This, in turn, promotes concentration of liquidity trades and generates even greater trade volume and more volatility. Similarly, Kim and Verrecchia (1997) argue that public announcements increase information asymmetry because investors have varying degrees of skill in interpreting news. This implies that the news impact on volatility dominates the effect on prices, with volatility remaining at elevated levels long after prices have adjusted.

In addition, responses to macroeconomic announcements may also vary depending on the overall level of volatility in the market. In our sample, volatility increased sharply with the onset of the financial crisis in the United

[3]Systemically important countries are defined as economies that have the potential to significantly affect markets and economies around the globe through a variety of channels.

States in the summer of 2007. In line with the findings in Andritzky et al. (2007), we would expect market reaction to macroeconomic news to become more difficult to detect during financial turbulence, because investors are expected to engage in more active and frequent repositioning of their portfolios, despite declining trading volumes.

These hypotheses are largely confirmed by the analysis, although some caveats apply. As in studies of mature markets, we find that the initial price adjustment upon the arrival of new information is weak and dissipates within minutes of the announcement. The direction and magnitude of the response is broadly similar for emerging and U.S. bonds at very high frequencies (one-minute intervals). As expected, the volatility response is much more pronounced than the price response. Volatility remains at elevated levels, at up to six times the preannouncement level, for up to three hours after the announcement—about three times longer than in mature bond markets. This result confirms that the absorption of new information is occurring much more slowly in emerging markets than in mature markets. Although responses to news vary to some extent across countries and types of indicators, international news (from systemically and regionally important countries) is generally at least as important as domestic news for both asset valuations and volatility dynamics in emerging markets. Moreover, we find evidence of asymmetric effects (stronger responses to negative news than to positive news) and observe a disproportionately large impact of news releases that contain large surprises. As average volatility has increased with the onset of the subprime crisis, the impact of international (U.S.) news has become more muted, possibly reflecting a perception that emerging economies are likely to be resilient to the U.S. downturn.

The rest of the chapter is organized as follows. After reviewing the literature in Section 4.2, Section 4.3 describes the high-frequency data on bond prices and macroeconomic announcements and also explains how the surprise content of news was measured. The intraday return volatility patterns and the important structural break in the data generating process due to the onset of the subprime crisis are discussed in Section 4.4, along with their implications for the modelling framework, as detailed in Section 4.5. The empirical findings concerning the effect of macroeconomic news on prices and volatility are presented in Section 4.6. Section 4.7 concludes.

4.2 Literature Review

The literature on mature markets provides a useful benchmark for the analysis of the market microstructure related to emerging market assets. In one of the most comprehensive studies on the topic, Andersen et al. (2003) examine the role of fundamentals in high-frequency movements in the U.S. dollar spot exchange rates. They find that surprises in macroeconomic data releases have a significant effect on five-minute returns. This finding implies, in line with theoretical models of market microstructure (see O'Hara, 1995, and the references therein), that news about fundamentals is quickly incorporated into asset prices. Market reactions are asymmetric: that is, bad news has a greater impact on markets than good news. Bauwens et al. (2005b) confirm the latter finding, using headlines released on Reuters screens as a measure of news. They also examine how news affects volatility, but do not detect any significant post-announcement effects. In contrast, earlier studies by Ederington and Lee (1993) and Fleming and Remolona (1999) reported strong bond market volatility in response to macroeconomic releases. For stock markets, Andersen et al. (2000) also find that macroeconomic announcements have an instantaneous impact on the volatility of five-minute returns on the Nikkei 225 index.

Mature markets appear to respond to public information in a multi-stage process. Prices do not always react to announcements, but, when they do, the adjustment occurs within one minute of the announcement, implying a high information efficiency of mature financial markets. Trading activity, as reflected in the volatility of prices, rises within ten to fifteen minutes of the announcement and remains elevated for about an hour. Bid-ask spreads widen in tandem with the increase in trading activity but narrow before trading activity subsides, suggesting that the initial stages of adjustment are dominated by informed trading, whereas the last stages are driven by liquidity trading (Fleming and Remolona, 1999; and Balduzzi et al., 2001).

Regarding the type of fundamentals that markets focus on, the literature on mature markets suggests that news about local macroeconomic indicators that are considered to be good predictors of the cyclical position of the economy and policy actions matters most, although news about fundamentals in systemically important foreign countries also affects prices and volatility. The timeliness and incremental information content of news also matters. In a study of ten-minute returns in U.S. futures markets, Veredas (2006) finds that traders show less interest in macroeconomic indicators that are released with a long delay—for example, gross domestic product (GDP) data—than more frequent releases—such as those of the consumer price index (CPI), employment, industrial production, and factory orders.

4.3 Intraday Price Data and Announcements

The core of our emerging market data set consists of intraday price data for the benchmark external bonds issued by Brazil, Mexico, Russia and Turkey. Together with Argentina and Venezuela (which we exclude because of data problems), these four countries represent the top six sovereign issuers among emerging economies (Trade Association for the Emerging Markets, 2008; JPMorgan, 2008). Their benchmark bonds are among the most liquid and actively traded instruments in the asset class. We compare the data for these four countries with similar, high-frequency data on a U.S. treasury note to quantify differences between reaction of mature and emerging bond markets to news. Data on expectations and announcements of local macroeconomic data and interest rate decisions are used as a proxy for public information about macroeconomic fundamentals. For international macroeconomic data, we use announcements for the United States; for Russian and Turkish bonds we also use regional data, those for Germany. The sample period is from October 1, 2006, to February 20, 2008 (297-340 trading days during 17 months, depending on the bond), split into two subperiods: before and during global financial turmoil triggered by the U.S. subprime market crisis, whose onset is identified as June 5, 2007 (see below). The main data source is Bloomberg.

4.3.1 Intraday bond prices

We focus on the benchmark bonds for each of the four countries. The Brazilian 11 percent 2040 bond with an outstanding volume of USD 4.2 billion is by far the most liquid emerging market bond with an annual trading volume of USD 215 billion in 2007. The high liquidity of this bond is also reflected in its average bid-ask spread of USD 0.12 per USD 100 face value—the lowest among all Emerging Markets Bond Index Global (EMBIG) constituents. Mexico's external sovereign issuance comprises several liquid instruments. Among those, we choose the 5.625 percent 2017 as the largest issue, with an outstanding amount of about USD 3.5 billion and showing the lowest bid-ask spread (USD 0.22). Russia's 2030 bond is the largest Russian global issue, with an outstanding amount of USD 20 billion. This forms a significant weight of close to 8 percent in the EMBIG. It is also the second-most traded eurobond in the emerging market asset class, trading at an average bid-ask spread of about USD 0.23. Turkey's 11.875 percent 2030, the third-most traded emerging market eurobond, enjoys an annual trading volume of about USD 80 billion. Its outstanding value is USD 1.5 billion, making it the largest bond issued by Turkey, and the average bid-ask spread is reported to be USD 0.42. For comparisons with mature markets' behaviour, this data set for emerging market bonds is complemented by tick-by-tick data for the corresponding on-the-run ten-year U.S. treasury note provided by Tullett Prebon, an interdealer broker. These intraday data are comparable to GovPx data, which are often used in the literature on mature markets.

The primary price data on emerging market bonds are ten-minute mid-quotes, where the mid-quote is an average of the bid and ask prices available on Bloomberg, one of the most widely used information systems for bond traders. Most trading in emerging market bonds takes place over-the-counter (OTC), and bid-ask quotes from Bloomberg are considered reliable, and most importantly, tradable. Further, evidence from other OTC markets, such as foreign exchange markets, indicates that returns constructed from quotes and trade data closely follow each other, especially when sampled every ten minutes (see Goodhart et al., 1996; and Daníelsson and Payne, 2002). Ten-minute intervals are also preferred because trading activity is limited at shorter time intervals. However, we also construct a secondary dataset that consists of one-minute return series from quotes posted between 8.00 and 9.00 a.m. Eastern Standard Time (EST) in the U.S., to study the impact of surprises in U.S. macroeconomic news on emerging and mature bond returns.

To get the data into a form suitable for analysis, we remove observations for quotes posted outside trading hours (assumed to be between 3.00 a.m. and 5 p.m. EST for Mexican and Brazilian bonds and between 2.00 a.m. and 5 p.m. EST for Turkish and Russian bonds), on weekends, on major U.S. and U.K. public holidays, and on days when 95 percent or more of returns are zero. To minimize data errors, we exclude bid and ask quotes with non-positive prices, observations for which the absolute bid/ask price change is greater than 10% of the previous bid/ask price (Huang and Stoll, 1994)) and the obvious jumps from the U.S. treasury note data, which characterize about 3 percent of our sample (see Mizrach and Neely, 2007, for a discussion of discontinuities in the U.S. treasury data). Finally, we replace overnight returns with their unconditional means, to remove overnight, weekend and public holiday effects (see Andersen and Bollerslev, 1997b, and Engle and Russell, 1998).

Table 4.1 provides information on the sample sizes, liquidity (defined here as the average number of bid/ask quotes arriving per trading day, see for example Andersen et al., 2007a) and data summary statistics for the one- and ten-minute return series. Within our sample, the Russian and Turkish bonds are the most liquid EM bonds, with the average number of bid/ask quotes arriving per trading day equal to 236 and 230 over the full sample period. However, the liquidity in the Latin American bonds increased two- to four-fold during the subprime crisis, to levels comparable with the liquidity in the other two bonds. The average returns are, as expected, zero for both one- and ten-minute series, with the standard deviation ranging from 0.3 basis points for one-minute U.S. returns to 2.3 basis points for ten-minute Mexican returns. Generally, the Latin American returns are the most variable. Apart from the ten-minute Brazilian series, the return distributions are negatively skewed, and all the distributions show excess kurtosis. Moreover, the data display small negative first-order autocorrelation. The summary statistics for the absolute returns also indicate that the U.S. T-note returns are the least volatile with the average absolute return equal to 0.2 basis points.

4.3.2 Macroeconomic announcements and expectations

Releases of macroeconomic data and market expectations for Brazil, Mexico, Russia, and Turkey, as well as for Germany and the United States, are also obtained from Bloomberg. Given the large number of data releases, especially for the United States and Germany, the sample is restricted to the most relevant items, in line with other studies, such as that by Andersen et al. (2003). The selection of macroeconomic data is guided by timeliness, economy-wide relevance, and frequency of releases (we require at least four announcements during the sample period), as well as the availability of analyst forecasts. The selection is confirmed through a survey of the IMF's country desks.

Information on macroeconomic developments in a given period is released in stages: releases of high-frequency data (for example, monthly data on CPI, PPI, industrial production and retail sales) are followed by releases of quarterly

Table 4.1: Summary Statistics for One- and Ten-Minute Bond Returns

	Brazil		**Mexico**		**Russia**		**Turkey**		**U.S.**	
	10min	*1min*	*10min*	*1min*	*10min*	*1min*	*10min*	*1min*	*10min*	*1min*
Sample sizes										
Number of trading days	325		297		324		325		340	
Proportion of 8:00 – 9:00 quotes	9.92%		10.77%		11.06%		10.16%		8.27%	
Number of observations	27,300	19,500	24,948	17,820	29,160	19,440	29,250	19,500	30,600	20,340
Liquidity	166	18	210	25	236	29	230	26	659	55
— before crisis	60	9	129	21	188	27	170	18	561	52
— during crisis	246	25	276	29	272	31	276	32	751	58
Returns										
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Standard deviation	0.019	0.011	0.023	0.013	0.015	0.007	0.022	0.009	0.006	0.003
Skewness	0.064	-0.070	-0.101	-0.431	-0.743	-2.784	-0.325	-0.818	-0.171	-0.588
Kurtosis	19.662	37.326	19.463	54.091	36.969	110.237	29.096	64.022	14.501	53.033
First-order autocorrelation	-0.171	-0.190	-0.203	-0.095	-0.144	-0.091	-0.084	-0.088	-0.053	0.055
Absolute returns										
Mean	0.009	0.003	0.010	0.004	0.007	0.003	0.011	0.003	0.004	0.002
Standard deviation	0.017	0.010	0.021	0.012	0.014	0.007	0.019	0.008	0.004	0.003
Skewness	3.486	5.232	3.648	6.254	4.927	7.271	4.532	6.371	3.320	6.063
Kurtosis	23.503	38.371	21.000	59.196	49.653	152.215	37.039	76.977	25.351	89.928
First-order autocorrelation	0.253	0.224	0.317	0.196	0.265	0.148	0.210	0.218	0.253	0.223

Notes: The table reports sample sizes and summary statistics for the ten-year U.S. treasury note and emerging market external bonds: Brazil 2040, Mexico 2017, Russia 2030, and Turkey 2030. Quotes posted outside trading hours (assumed to be 3.00 a.m. – 5.00 p.m. EST for Mexican and Brazilian bonds and 2.00 a.m.– 5.00 p.m. EST for Turkish and Russian bonds), during weekends, major U.S. and U.K. public holidays, and days with majority of zero ten-minute returns (95 percent or more) are removed from the sample. For the one-minute sample only quotes posted between 8.00 and 9.00 a.m. EST are retained. Liquidity is proxied by the average number of bid/ask quotes arriving per trading day over the period November 6, 2006 – February 20, 2008. he beginning of the the U.S. subprime market crisis is identified as June 5, 2007. For all assets, the differences in liquidity before and during the subprime crisis are significant at the 5% level. *Sample period:* October 1, 2006 – February 20, 2008. *Data sources:* Bloomberg, Tullett Prebon.

data (for example, on GDP). Many data releases follow a preannounced release schedule, in line with requirements of the IMF Special Data Dissemination Standard (SDDS), to which these countries subscribe.[4] Macroeconomic policy frameworks, as well as historical tradition, also bear on the composition of countries' data releases, as reflected, for example, in the emphasis Brazil and Mexico place on the frequent monitoring of prices, given their histories of hyperinflation. Regularity in the timing of data releases also varies across countries.[5] For example, Turkey and Mexico tend to schedule data releases at specific times, whereas releases in Brazil occur at multiple times during the day, with changing (though pre-announced) release times. Releases in Russia occur at irregular and not pre-announced times during the day.

Besides actual macroeconomic releases, we use data on markets' expectations of these releases. Bloomberg conducts surveys of market analysts in the week prior to a release. Analysts' median forecasts provide a measure of market expectations, comparable to those presented in Market Forecasts (formerly MMS).

4.3.3 Measures of surprise

In line with common practice in the literature (see, for example, Balduzzi et al., 2001; and Andersen et al., 2003 and 2007a), we calculate the standardized surprise associated with macroeconomic indicator k at time t as

$$S_{k,t} = \frac{\text{Actual}_{k,t} - \text{Expectation}_{k,t}}{\widehat{\sigma}_k}, \qquad (4.1)$$

where $\text{Actual}_{k,t}$ is the announced value of indicator k, $\text{Expectation}_{k,t}$ is the median market's expectation of k, and $\widehat{\sigma}_k$ is the standard deviation of all surprises ($\text{Actual}_{k,t} - \text{Expectation}_{k,t}$) for that macroeconomic series over the sample period. Thus, $S_{k,t} = 2$ implies a surprise that is two standard deviations greater than zero for that particular indicator. The calculation measures the size and direction of "news," and the standardization allows for meaningful comparisons of the estimated news effects regardless of different units of measurement (Andersen et al., 2003). We use the magnitude of

[4] The Special Data Dissemination Standard (SDDS) was established in 1996 as a guide for the provision of economic and financial market data. It requires subscribers to observe good practices for data coverage, periodicity, quality, integrity and timeliness and to provide the public with access to the data.

[5] Spot checks of news ticker items provide confidence that release times, as saved by Bloomberg, are sufficiently precise to be usable for the analysis of ten-minute bond returns.

surprises when estimating the impact of news on mean returns, with a prior that, consistent with economic intuition, larger news surprises would trigger larger price movements.

We also consider release time indicators $A_{k,t}$ as a measure of information arrival. The motivation for including the news arrival dummies is twofold. Firstly, Andersen et al. (2003 and 2007a) report that volatility response is more consistently induced by the arrival of information rather than by the magnitude of surprises and that including news announcement dummies in the volatility equation rather than the absolute values of the news surprise components improves model fit. Secondly, this approach facilitates the analysis of the effects of macroeconomic releases for which few analysts' forecasts are available. For example, there are no market expectations for consumer credit in Brazil or the current account balance in Russia, and only 12 out of 16 Turkish unemployment statistics are accompanied by relevant market forecasts. Table 4.2 provides a summary of the macroeconomic news announcements included in the study and the total number of releases and market expectations. The number of considered releases varies between 152 for Turkey to 403 for Brazil, which provides a range of inflation statistics. Market expectations are available for at least 80% of the releases (Turkey), with virtually all new German, Mexican and U.S. announcements being accompanied by the corresponding survey data.

4.4 Preliminary Data Analysis

This section provides a preliminary investigation of our high-frequency financial data that motivates our modelling framework in Section 4.5. There are two data characteristics that have important implications for our modelling framework: the intraday seasonality in the volatility series and the striking structural break in the data generating process due to the onset of the subprime crisis in June 2007.

Intraday financial variables, such as volatility, bid/ask spreads, durations, and trade frequencies, are well known for their characteristic intraday seasonality, see for example Baillie and Bollerslev (1989), Andersen and Bollerslev (1998), Engle and Russell (1998), and the analysis in chapter 2. Figure 4.1 attests that systematic time-of-day patterns are also present in the emerging market external bonds considered in our study. A visual inspection of patterns

Table 4.2: Macroeconomic News Announcements

	Brazil		Mexico		Russia		Turkey		U.S.		Germany	
	Obs.	*Exp.*	*Obs.*	*Exp.*	*Obs.*	*Exp.*	*Obs.*	*Exp.*	*Obs.*	*Exp.*	*Obs.*	*Exp.*
GDP	5	5	5	5	7	7	5	5	11	11	6	6
Industrial production	16	16	14	14	16	16	15	15	16	16	17	17
Personal consumption									16	16		
Investment			16	16	14	14						
Current account	14	13			5		14	14	5	5	17	17
Trade balance	67	16	24	22	42	33	15	15	17	17	51	51
Public budget balance	15	15	14	14	15				17	17		
Net debt & reserves	15	15			15	15						
Durable goods orders									16	16		
Factory orders									17	17	17	17
Capacity utilization							16	15	16	16		
Inventories									17	17		
Retail sales	14	14	13	13	14	14	13		17	17	16	16
Personal spending									16	16		
Personal income					14	14			16	16		
Consumer credit	11								16	16		
Housing indicators									60	55		
Economic indicator			13	13					16	16	16	16
Industry indices									51	51	51	51
Consumer confidence			14	14			13		16	16		
CPI	336	288	23	23	64	55	15	15	32	32	32	32
PPI					14	14	15	15	15	15	33	30
Real wages					14	13						
Unemployment	12	12	13	13	14	14	16	12	88	88	16	16
Interest rate	9	9	13	13			15	15	8	7	17	17

(cont.)

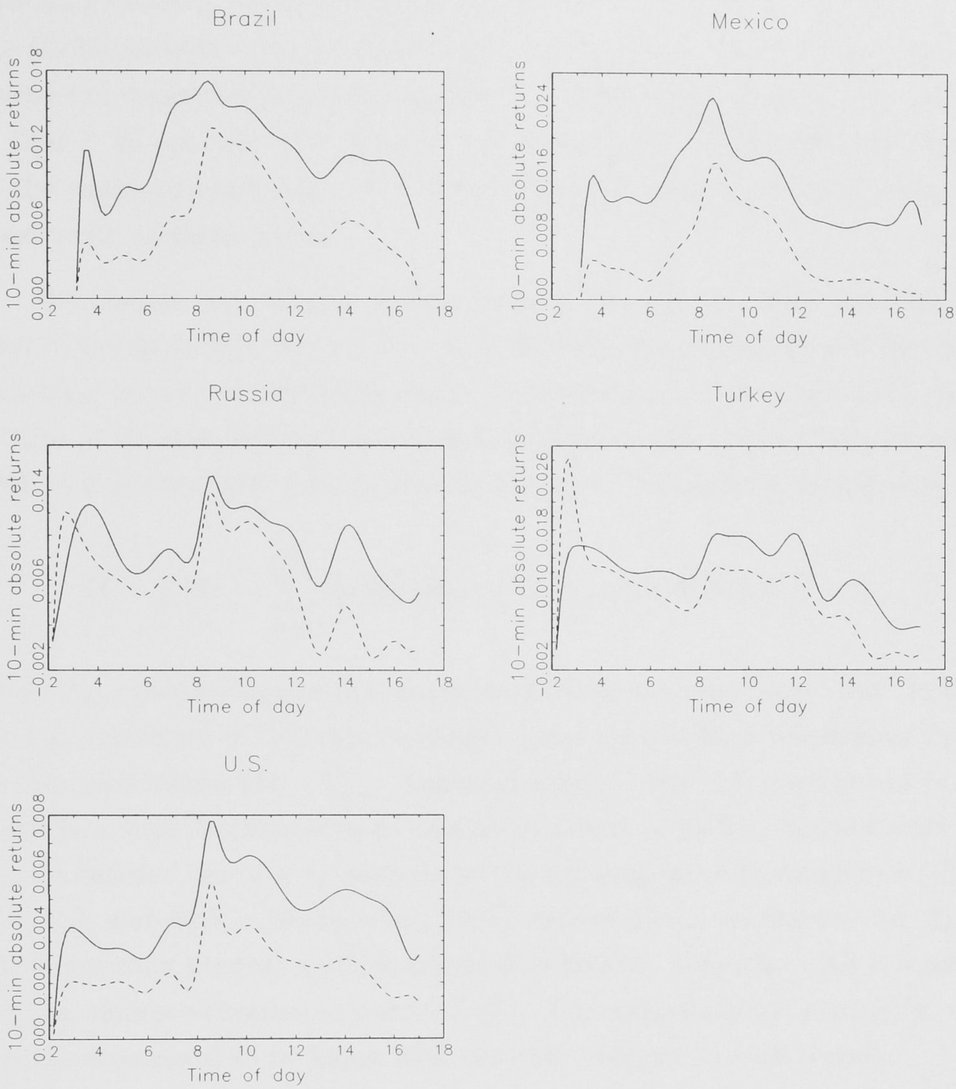
Table 4.2: Macroeconomic News Announcements *(table notes)*

Notes: The table provides a summary of the macroeconomic news announcements included in the study and the total number of releases (*Obs.*) and market expectations (*Exp.*). For Brazil, trade balance includes separate series of weekly and monthly releases; CPI: Getúlio Vargas Foundation (FGV) Market General Price Index (final and preliminary), FGV Prices General Index–Internal Availability, FGV Consumer Price Index, Foundation Institute for Economic Research (FIPE) Consumer Price Index (weekly and monthly), Brazilian Institute of Geography and Statistics (IBGE) National Consumer Price Index, and IBGE Amplified Consumer Price Index. Private bank lending is used instead of consumer credit. Net debt & reserves report the net debt. For Mexico, trade balance and CPI include separate series of preliminary and final releases. For Russia, CPI includes separate series of month-on-month, year-on-year, and year-to-date CPI, and core CPI; trade balance: imports, exports, and trade balance. Disposable income is used instead of personal income. Net debt & reserves report the reserves. For Turkey, tourist arrivals are used instead of retails sales. For the U.S., GDP includes separate series of advance and preliminary releases; personal consumption: advance, preliminary, and final releases; housing indicators: building permits, housing starts, new home sales, and the S&P/ Case-Shiller index; industry indices: the ISM Manufacturing and Non-Manufacturing indices; CPI: consumer and core consumer price indices; unemployment: initial jobless claims and nonfarm payroll. The interest rate is the Federal Open Market Committee target interest rate. For Germany, PPI includes separate series of producer and wholesale price index releases; trade balance: imports, exports, and trade balance; industry indices: the Purchasing Manager Manufacturing and Services indices, and the ZEW Financial Expert Survey. The interest rate is the European Central Bank interest rate. *Sample period:* October 1, 2006 – February 20, 2008. *Data source:* Bloomberg.

in the return volatility (defined as absolute values of ten-minute returns) highlights systematic time-of-day seasonality, with volatility rising during the opening hours of the U.K. and U.S. markets (around 2 a.m. and 9 a.m. EST, respectively). We assume that the intraday behaviour can be approximated by a cubic spine. Splines are piecewise polynomial smoothing functions that are often employed to model intraday seasonality in high-frequency financial data (see De Boor, 1978, and Eubank, 1988, for a general treatment of splines). Following Engle and Russell (1998), we set the knots at each hour and add an extra knot at 8.30 a.m. to control for the opening of the U.S. market. Intraday volatility follows an inverse U-shaped pattern, which is characteristic of mature markets as well (see Andersen and Bollerslev, 1998, and the references therein). The mean of intraday absolute returns peaks during the U.S. market opening. Given the concentration of OTC trading in New York and London, intraday patterns are comparable to those in foreign exchange markets, with spikes occurring during the U.S. and U.K. openings, particularly for euro-denominated Russian and Turkish bonds. We also use separate splines for Mondays and Fridays to control for some weekly patterns present in the data, Fridays seem to be the most volatile days, Mondays—the least.

Intraday volatility behaviour also differs before and during financial crisis (compare the dashed and solid lines in Figure 4.1, respectively). Before the crisis, the U.S. market opening was associated with an increase in volatility, but differences in volatility during the openings of the U.K. and U.S. markets diminish during the crisis. Average daily volatility increased across all

Figure 4.1: Intraday Volatility Patterns Before and During the Subprime Crisis



Notes: The figure graphs the intraday patterns of return volatility (defined as absolute ten-minute returns) for the U.S. ten-year Treasury note and emerging market external bonds: Brazil 2040, Mexico 2017, Russia 2030 and Turkey 2030. The dashed lines represent the intraday volatility patterns pre-crisis, and the solid lines—during the crisis. Both estimates are obtained using cubic splines with hourly knots, with an extra knot at 8.30. The beginning of the the U.S. subprime market crisis is identified as June 5, 2007. The time of the day is measured in hours since midnight, Eastern Standard Time. *Sample period:* October 1, 2006 – February 20, 2008. *Data sources:* Bloomberg, Tullett Prebon.

emerging markets during the financial crisis, pointing to increased market activity,[6] heightened uncertainty, and, possibly, weaker information efficiency. To control for differences in volatility, we include separate cubic splines for the crisis period in the model.

[6]Despite falling aggregate trade volumes, as measured by the Trade Association for the Emerging Markets.

To formally identify the start of the financial crisis, we employ a Markov-switching vector autoregression model. The general idea behind regime-switching models, introduced by Hamilton (1989), is that the parameters of the H-dimensional vector of return series $\mathbf{R}_t = (R_{1t}, \ldots, R_{Ht})'$ depend upon a stochastic, unobservable regime variable θ_t, which defines the regime prevailing at time t. In our case $H = 4$, as we are searching for a joint structural break in the emerging bond data. We control for changes in the U.S. government bond yield, as shown below.

We assume two regimes with a singular jump in the time series at the start of the financial crisis, i.e. $\theta_t = 1, 2$. We then fit a mean-adjusted Markov-switching vector autoregression model of lag order $p = 2$ to logarithmic daily returns of the four external emerging bonds over a time period from January 2006 to February 2008 (544 daily observations). The model is specified as

$$\mathbf{R}_t - \mu(\theta_t) = \sum_{p=1}^{2} \mathbf{B}_p(\theta_t)(\mathbf{R}_{t-p} - \mu(\theta_{t-p})) + \mathbf{A}(\theta_t) X_{t-1} + \nu_t,$$

where X_{t-1} denotes lagged changes in the U.S. government bond yield. In this setting, the vector of the selected sample bond returns $\mathbf{R}_t$ is conditional upon its own past values $\{\mathbf{R}_{t-w}\}_{w=1}^{\infty}$, lagged changes in the U.S. government bond yield X_{t-1}, and the (unobserved) regime variable $\theta_t = \{1, 2\}$. For each state θ_t, $\mathbf{B}_p(\theta_t)$ denotes the (4×4) matrices of the autoregressive parameters for lags $p = 1, 2$, and $\mathbf{A}(\theta_t)$ denotes the (4×1) vectors of the coefficients for X_{t-1}. The innovation process $\nu_t \mid \theta_t$ is assumed to be i.i.d. Gaussian with a regime-varying variance-covariance matrix $\Sigma(\theta_t)$. For computational simplicity, the process is assumed to be linear with constant variance in each regime.

A complete description of the data-generating mechanism requires specifying the stochastic process that generates θ_t (i.e. the "switching mechanism") and its effect on $\mathbf{R}_t$. Following Hamilton (1989), we parameterize θ_t as a discrete-state, first-order Markov process with a (2×2) transition matrix $\mathbf{P} = \begin{pmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{pmatrix}$, $p_{i1} + p_{i2} = 1$ for each state. The transition probabilities are defined as

$$p_{ij} = \Pr(\theta_t = j \mid \theta_{t-1} = i, \mathbf{R}_{t-1}, \mathbf{X}_{t-1}) \quad \forall i, j \in \{1, 2\}.$$

We estimate the joint transition probability matrix to be $\mathbf{P} = \begin{pmatrix} 0.8104 & 0.7041 \\ 0.1896 & 0.2959 \end{pmatrix}$, and identify June 5, 2007 as the most likely date of the structural break.

4.5 Two-Stage Modeling of Returns and Volatility

Following Andersen and Bollerslev (1998) and Andersen et al. (2003 and 2007a), we use a two-step weighted least-squares (WLS) approach to simultaneously model the dynamic effects of a broad range of macroeconomic announcements on the returns and volatility of emerging market bonds.[7,8] The approach can be summarized as follows. Let R_t be a ten-minute logarithmic return for a single bond series, $t = 1, \ldots, T \cdot N$, where T is the number of calendar days in the sample and N is the number of ten-minute returns within each trading day. We model the conditional mean as

$$R_t = \beta_0 + \sum_{i=1}^{I} \beta_i R_{t-i} + \sum_{k=1}^{K} \sum_{j=0}^{J} \beta_{kj} S_{k,t-j} + \varepsilon_t, \tag{4.2}$$

where the standardized surprise associated with macroeconomic indicator k, $S_{k,t}$ is defined by (4.1). The lag length I and the response length J are determined using model selection criteria, and we also test whether coefficients change during the financial crisis period (see below).

The ordinary least squares (OLS) estimation of equation (4.2) would yield asymptotically consistent but inefficient estimates, because the variance of return innovations, ε_t, is time-varying.[9] To deal with this inefficiency, we first model time-varying volatility of return innovations. We then use the reciprocal of the fitted volatility series as weights for the WLS estimation of the mean

[7] For other applications of this approach, see Andersen et al. (2000); Bollerslev et al. (2000); Dominguez (2006); and Wongswan (2006).

[8] The alternative, one-stage approach requires estimating a large set of GARCH parameters in a simultaneous model of intraday returns and volatility. That approach has been used in studies that focus on the impact of a narrow set of announcements or news intensity. The latter is often proxied by the number of headlines arriving on Bloomberg or Reuters screens. For examples of the one-stage approach, see Chang and Taylor (1998 and 2003); Gau and Hua (2007); DeGennaro and Shrieves (1997); and Melvin and Yin (2000).

[9] See Mandelbrot (1963) for an early discussion of volatility clustering, i.e. the tendency for large (small) return innovations to be followed by other large (small) return innovations, Bollerslev (2001) for an overview of the time-varying volatility studies.

equation (4.2) and thus obtain the correct standard errors of the parameters in (4.2).

Absolute return residuals $|\widehat{\varepsilon}_t|$ are used as a proxy for the volatility process; a theoretical motivation for using absolute returns instead of squared returns is provided by Forsberg and Ghysels (2007). The proxy for intraday volatility is assumed to follow the following multiplicative process:

$$|\widehat{\varepsilon}_t| = h\,(\text{deterministic volatility}) \cdot g\,(\text{stochastic volatility}) \cdot u_t, \tag{4.3}$$

where u_t is independent, identically distributed (i.i.d.) with unit mean and unit variance. The deterministic volatility is the seasonal component of intraday and week effects that we allow to vary during the financial crisis. As mentioned above, this behaviour is modeled using cubic splines $\phi(t)$ with hourly knots and an extra knot for 8.30 a.m. EST. The stochastic volatility is assumed to be a function of the short- and long-run persistence effects, and announcements effects. More specifically, the functional form of equation (4.3) is

$$\ln|\widehat{\varepsilon}_t| = (\alpha + \phi(t)) + \left(\psi\sigma_{d(t)} + \sum_{i=1}^{I'} \beta_i \ln|\widehat{\varepsilon}_{t-i}| + \sum_{k=1}^{K}\sum_{j'=0}^{J'} \beta_{kj'} A_{k,t-j'}\right) + \ln u_t, \tag{4.4}$$

where the left-hand-side variable, $\ln|\widehat{\varepsilon}_t|$, is the logarithm of the absolute value of the residual of equation (4.2), and $\sigma_{d(t)}$ is the daily volatility over the day containing the ten-minute return t, that captures the long-run persistence effects (Andersen and Bollerslev, 1998). We proxy $\sigma_{d(t)}$ with the average of ten-minute absolute return innovations over the previous day, i.e. $d(t-1)$.[10] Finally, the short-run persistence effects, or autoregressive, conditionally heteroskedastic (ARCH) effects, are estimated using the lags of $\ln|\widehat{\varepsilon}_t|$. As above, the ARCH lag length I' and the response length J' are determined using model selection criteria.

We determine the lag structure in the conditional mean equation by testing for up to six hours of autoregressive (AR) effects and for different coefficients during the financial crisis. These tests are performed with no news variables included in the model. The best model specifications are chosen based on Akaike (AIC) and Bayesian (BIC) information criteria. Whenever

[10] We also tried to proxy $\sigma_{d(t)}$ with one-day-ahead predictions from a daily generalized autoregressive, conditionally heteroskedastic GARCH(2,2) model, as advocated by Andersen et al. (2003). We chose the estimator based on the average of ten-minute absolute return innovations over the previous day $d(t-1)$ because it fits the data better, as judged by the AIC and BIC statistics.

Table 4.3: AR-ARCH Specification

	Brazil	**Mexico**	**Russia**	**Turkey**	**U.S.**
AR	AR(9)	AR(16)*	AR(7)*	AR(8)*	AR(1)*
ARCH	ARCH(13)*	ARCH(18)*	ARCH(8)*	ARCH(18)*	ARCH(9)*

Notes: The lag structure of the conditional mean and variance equations for emerging market external bonds and the ten-year U.S. treasury note is determined within the following framework:

$$R_t = \beta_0 + \sum_{i=1}^{I} \beta_i R_{t-i} + \varepsilon_t,$$

$$\ln|\hat{\varepsilon}_t| = \alpha + \phi(t) + \psi\sigma_{d(t)} + \sum_{i=1}^{I'} \beta_i \ln|\hat{\varepsilon}_{t-i}| + \ln u_t,$$

where R_t is the ten-minute log-return, $\sigma_{d(t)}$ is the long memory volatility over the day containing the ten-minute return t, and $\phi(t)$ is the seasonal component of intradaily and weekly effects that we allow to vary during the period of the subprime crisis. This behaviour is modeled using cubic splines with hourly knots (and an extra knot for 8.30 a.m. EST). We test for up to six hours (i.e. 60 lags) of autoregressive (AR/ARCH) effects for indicators I and I' in the conditional return and volatility equations, and for different coefficients during the subprime crisis. At this stage, no news variables are included in the model. The best model is chosen by AIC and BIC criteria. Whenever there is a conflict between these two criteria, we use the F-test to decide between the two models. This table reports the AR-ARCH specification of the models, with $*$ denoting that coefficients are allowed to change during the crisis period. *Sample period:* October 1, 2006 – February 20, 2008. The beginning of the U.S. subprime market crisis is identified as June 5, 2007. *Data sources:* Bloomberg, Tullett Prebon.

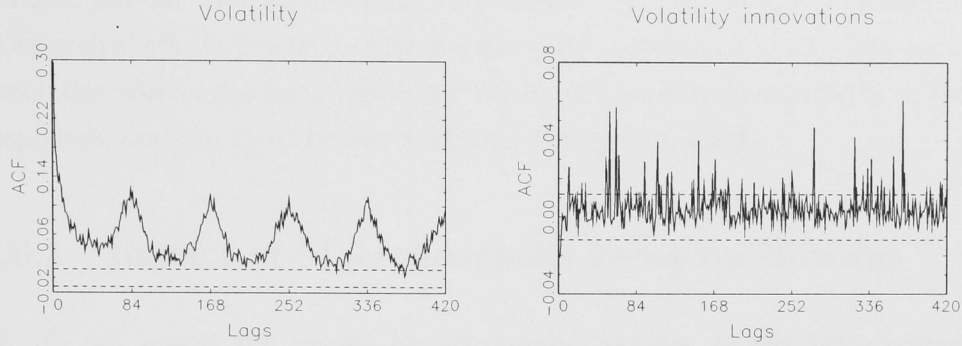
there is a conflict between the selection criteria, we use the F-test to decide between the two models. The ARCH structure of the stochastic volatility is determined in a similar manner as the AR structure. The best models that emerge following the tests are presented in Table 4.3.

Further, we allow the data to determine both the length of the response to news for the conditional mean and volatility equations and any differences in the response during financial turbulence. In line with Andersen et al. (2003), we test for periods from zero minutes (i.e., without lagged response) to three hours. Guided by the AIC and BIC criteria, we uniformly choose to model the impact of news on the returns without lagged response, but allow for 30 minutes of lagged news effects in the volatility equations (i.e. $J = 0$ and $J' = 3$ for each asset). We also do not allow the individual news coefficients to change during the period of financial turbulence.

The resulting model appears well specified. On average, the correlation between the observed and the fitted volatility series is 0.35. The volatility residuals $\hat{u}_t$ is i.i.d. (see Figure 4.2 for an example of autocorrelation patterns in observed volatility and residuals). There is some remaining autocorrelation in residuals from equation (4.4), but we ensure the robustness of the standard errors and the validity of hypothesis testing by using the heteroscedasticity- and autocorrelation-consistent (HAC) standard errors, obtained using the Newey-West procedure.

The key in estimating equation (4.4) is to ensure that the fitted volatility

Figure 4.2: Autocorrelation of Ten-Minute Return Volatility and Volatility Innovations



Notes: The solid lines represent the autocorrelation function for ten-minute return volatility (left panel) and volatility residuals $\hat{u}_t = |\hat{\varepsilon}_t| / \hat{\sigma}_t^2$ (right panel) for a sample bond (Brazilian 2040 Bond). The dashed lines represent 95% confidence intervals. 84 lags correspond to one trading day and 420 lags correspond to one trading week. *Sample period:* October 1, 2006 – February 20, 2008. *Data sources:* Bloomberg, Tullett Prebon.

innovations $\widehat{u}_t$ are i.i.d. random variables, that is, without any autocorrelation or heteroscedasticity. These assumptions are satisfied in our data set in the multiplicative volatility model, as per equation (4.4). In contrast, the additive volatility model that is common in the literature on mature markets (see for example Andersen et al., 2003 and 2007a) does not capture the deterministic behaviour of the emerging assets as well as the multiplicative volatility model.

4.6 Emerging Markets' Reaction to News

We estimate the news response model for emerging market external bonds and the ten-year U.S. treasury note as

$$\begin{aligned} R_t &= \beta_0 + \sum_{i=1}^{I} \beta_i R_{t-i} + \sum_{k=1}^{K} \beta_k S_{k,t} + \varepsilon_t, \\ \ln|\hat{\varepsilon}_t| &= \alpha + \phi(t) + \psi\sigma_{d(t)} + \sum_{i=1}^{I'} \beta_i \ln|\hat{\varepsilon}_{t-i}| + \sum_{k=1}^{K} \sum_{j'=0}^{3} \beta_{kj'} A_{k,t-j'} + \ln u_t, \end{aligned}$$

where R_t is the ten-minute log-return, $\phi(t)$ is a cubic spline that estimates the intradaily and weekly seasonality, $\sigma_{d(t)}$ is the long memory volatility over the day containing the return t, $S_{k,t}$ is the standardized news corresponding to a macroeconomic fundamental k released at time t, $A_{k,t}$ is a dummy variable indicating the release of this fundamental, and I and I' denote the autoregressive (AR/ARCH) effects, as specified in Table 4.3.

In this section we discuss various aspects of information absorption in emerging bond markets. We start by examining the impact of macroeconomic news on ten- and one-minute returns (subsection 4.6.1). We then consider how news arrival affects ten-minute return volatility (subsection 4.6.2). The section concludes with a discussion of many nonlinearities and asymmetries in these responses, and the cross-border spillovers (subsection 4.6.3).

4.6.1 Impact of Macroeconomic News on Returns

We do not report the results for ten-minute returns, as the price response to surprises in macroeconomic news is mostly insignificant. There is little systematic evidence in ten-minute return data that macroeconomic surprises are causing distinctive price shifts. Moreover, there are few indicators that significantly contribute to explaining the conditional mean, and even these effects are not consistent across countries.

One possible reason for this finding is that the economic interpretation of macroeconomic news is not straightforward for sovereign bond markets and, particularly, for emerging bond markets. For example, a positive surprise about a country's trade balance (i.e., a trade deficit is larger than expected) can be a sign of either strength or weakness in macroeconomic fundamentals, depending on the factors driving the deficit and the degree of external vulnerability of the country in question. Macroeconomic forecasts for emerging economies also carry a larger margin of error because of the poorer quality and coverage of their statistics, as well as the more significant ongoing changes in the structure of emerging economies. In addition, short-term arbitrage trading may be less prominent in emerging bond markets than in mature bond markets because they are less liquid. The response of long-term investors also could be more protracted in emerging markets, where cross-over investors holding a broad range of asset classes account for a more significant share of the investor pool than dedicated investors.

The lack of evidence in ten-minute data does not imply that there will be no evidence in one-minute returns. Studies on mature markets show that returns react sharply to news for only the first few minutes (see Fleming and Remolona, 1999; and Andersen et al., 2007a). Such an immediate and short-lived effect would not be picked up in ten-minute interval data. We therefore follow Green (2004) and undertake a simple event study with one-minute returns, focusing on U.S. releases occurring between 8.00 and 9.00 a.m.

EST. Table 4.4 reports the contemporaneous and total impact of surprises in U.S. news, obtained by estimating the following model:

$$R_t = \beta_0 + \beta_1 R_{t-1} + \sum_{k=1}^{K} \sum_{j=0}^{3} \beta_{kj} S_{k,t-j} + \varepsilon_t, \tag{4.5}$$

where only the most recent lagged return is included in the model to keep the specification parsimonious while accounting for the bid/ask bounce (see Dacarogna et al., 2001, for discussion and stylized facts). The robust standard errors are estimated using the Newey-West procedure.

The contemporaneous effect reported in Table 4.4 denotes the percentage change in return when data about a macroeconomic indicator k is released (β_{k0}). We also calculate the total (accumulative) effect as the percentage change in return during the total observation window. We consider window lengths of one minute (i.e. no lagged response) to ten minutes, and find that the most significant after-release impact is observed within three minutes following an announcement. This implies that the total effect is calculated over a window of four minutes, as a sum of one-minute window of contemporaneous effect and three minutes of lagged response, i.e. ($\sum_{j=0}^{3} \beta_{kj}$).

Positive surprises in announcements of real activity indicators trigger price declines, as expected during a period near the peak of the economic cycle and rising price pressures. The magnitude of contemporaneous effects on returns varies between 8 and 108 basis points, in line with the empirical results of Almeida et al. (1998), who study the impact of macroeconomic announcements on deutsche mark/U.S. dollar exchange rate returns and report that payroll employment figures produce the strongest response of 30 basis points. Moreover, the direction and magnitude of responses are broadly similar for emerging and U.S. bonds (see Figure 4.3 for plots of the median response of one-minute returns to arrivals of U.S. GDP Advance statistics, core inflation reports and current account news[11]).

[11] The estimates of the impulse-response functions are obtained using Monte Carlo simulations and account for the parameter estimation uncertainty. In cases where AR and ARCH parameters are different before and during the subprime crisis period, the dynamics of the response change. However, the differences are negligible, and thus we plot the impulse response functions using the coefficient estimates and standard errors for the crisis period only.

Table 4.4: Impact of Surprises in U.S. Macroeconomic News on One-minute Returns

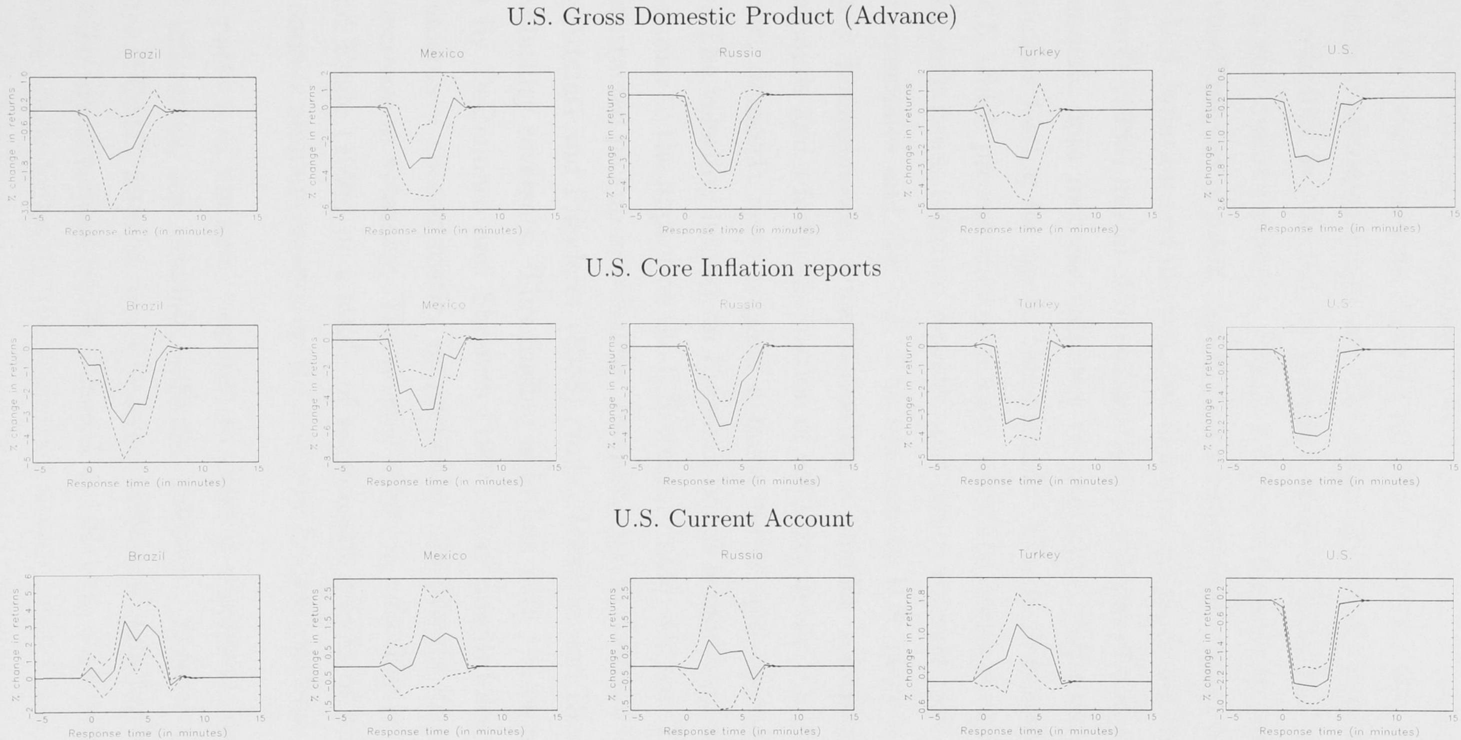
	Brazil		Mexico		Russia		Turkey		U.S.	
	ContEff	*TotEff*	*ContEff*	*TotEff*	*ContEff*	*TotEff*	*ContEff*	*TotEff*	*ContEff*	*TotEff*
GDP (Adv)	-0.160	**-1.517**	-0.040	**-3.367**	-0.051	**-3.674**	0.153	**-2.511**	-0.086	**-1.453**
Personal consumption (Adv)	**-0.085**	0.135	-0.140	0.015	-0.089	-0.039	0.045	-0.441	**-0.194**	-0.047
GDP (Pre)	0.609	0.481	-0.180	1.134	**0.780**	**-1.233**	-0.191	-0.041	-0.096	0.079
Personal consumption (Pre)	0.654	0.678	-0.580	-1.202	0.251	-0.247	-0.364	-0.506	-0.091	0.130
Current account	0.639	**3.391**	0.130	1.071	-0.062	0.491	0.217	**1.267**	-0.049	-0.141
Trade balance	0.136	0.448	0.040	**-1.157**	-0.124	-0.366	0.321	-0.344	-0.022	**-0.569**
Durable goods orders	0.085	-0.269	-0.320	-1.465	**-0.157**	-1.118	-0.508	**-1.316**	-0.078	**-0.938**
Retail sales	0.117	**-2.180**	-0.490	**-3.785**	-0.171	-1.172	-0.046	**-2.368**	-0.115	**-0.869**
Personal spending	-0.405	-0.671	0.040	-0.384	-0.076	**-0.949**	0.199	-0.334	-0.044	**-0.447**
Personal income	-0.164	**-1.861**	0.210	-0.471	0.139	0.014	-0.047	0.140	0.037	-0.013
Housing starts	**0.620**	-0.627	0.690	-0.829	**0.696**	-0.074	0.044	-0.625	0.118	**-0.748**
Building permits	0.247	0.223	**-1.040**	-0.473	-0.237	-0.093	0.039	0.304	**-0.187**	0.207
CPI	0.638	**-1.181**	**-1.030**	**-1.876**	0.030	0.638	-0.219	**-1.101**	-0.111	-0.457
Core CPI	**-0.735**	**-3.802**	0.060	**-4.893**	0.012	**-3.735**	0.116	**-3.458**	-0.185	**-2.255**
PPI	-0.316	-0.553	0.130	**-4.146**	0.626	-0.243	0.118	**-1.406**	0.035	**-0.960**
Unemployment	0.030	0.523	-0.200	0.266	-0.004	**0.760**	-0.176	0.454	-0.025	**0.596**

Notes: We estimate the news response model for emerging market external bonds and the ten-year U.S. treasury note,

$$R_t = \beta_0 + \beta_1 R_{t-1} + \sum_{k=1}^{K} \sum_{j=0}^{3} \beta_{kj} S_{k,t-j} + \varepsilon_t,$$

where R_t is the one-minute log-return on quotes posted between 8.00 and 9.00 a.m. EST, and $S_{k,t}$ is the standardized news corresponding to a U.S. macroeconomic announcement k made at 8.30 a.m. EST, $k = 1, \ldots, K$. *ContEff* denotes the contemporaneous impact of an announcement (β_{k0}). *TotEff* denotes the total impact of an announcement over the window of 3 minutes, calculated as $\sum_{j=0}^{3} \beta_{kj}$ and tested for significance using the χ^2 Wald statistic. Coefficients provided in **bold** are significant at the 5% level, using heteroscedasticity- and autocorrelation-consistent standard errors. *Sample period:* October 1, 2006 – February 20, 2008. *Data sources:* Bloomberg, Tullett Prebon.

Figure 4.3: Price Response to Surprises in U.S. Macroeconomic News



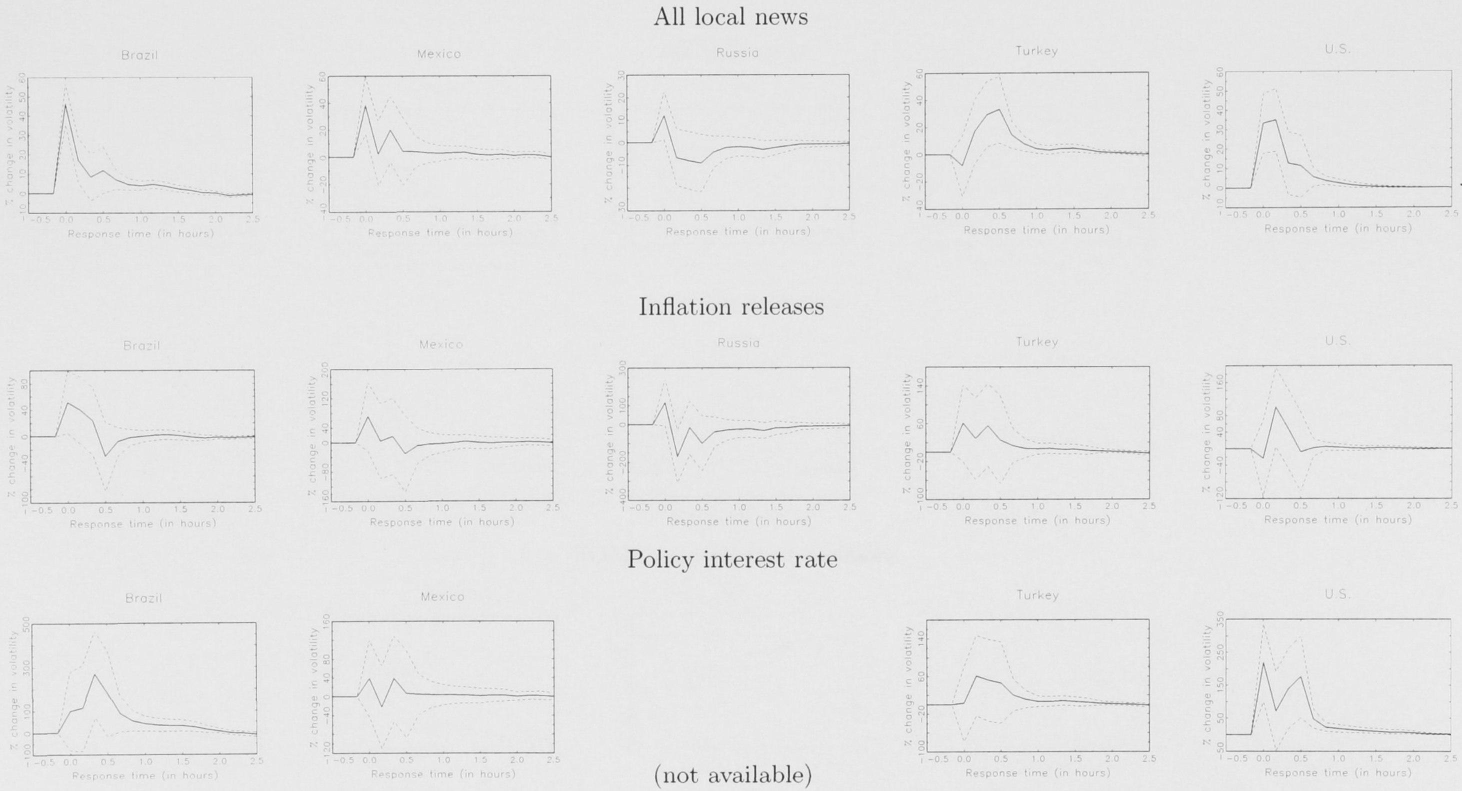
Notes: The figures present the one-minute return response to arrivals of U.S. GDP Advance statistics (top panel), core inflation reports (centre panel) and current account news (bottom panel). The solid lines represent the median percentage change in returns, and the dashed lines represent the 95% confidence intervals. The estimates are obtained using Monte Carlo simulations based on parameter estimates reported in Table 4.4 and account for the estimation uncertainty. The x-axis denotes time *in minutes*, with the announcements time fixed at 0. *Sample period:* October 1, 2006 – February 20, 2008. *Data sources:* Bloomberg, Tullett Prebon.

4.6.2 Impact of News Arrival on Return Volatility

The volatility response to the arrival of macroeconomic news, which reflects investors' repositioning in response to new information, is much more significant than the price response. Like Li and Engle (1998), who conclude that macroeconomic announcements are "the major source of price volatility," we find that volatility is affected by a broad range of local and global (U.S.) macroeconomic announcements. Figure 4.4 shows impulse-response functions for the overall impact of news, and Figure 4.5 shows the impact of news about local and U.S. inflation and interest rate changes. As predicted by the Admati and Pfleiderer (1988) model of intraday trading, releases of domestic and U.S. macroeconomic data increase volatility by one and a half times on average, with responses lasting for up to three hours. This is illustrated in Figures 4.4 and 4.5, which present the ten-minute volatility response to arrivals of all macroeconomic news, inflation reports, and policy interest rate decisions for domestic economies and the U.S. The reaction to U.S. news is pronounced and largely homogeneous, notwithstanding a smaller volatility reaction in Brazilian bonds and a faster dissipation of volatility in the U.S. treasury note. In contrast, domestic news triggers a more muted and more differentiated response. The volatility impact on Brazilian bonds is moderate and dissipates quickly, similar to the impact on the U.S. treasury note, whereas Turkish bonds show a protracted pickup in volatility. Interestingly, in contrast to predictions from the Admati and Pfleiderer (1988) model, Mexican and Russian markets exhibit volatility reversals. This finding is in line with the empirical results reported by DeGennaro and Shrieves (1997) that unscheduled policy news announcements— characteristic, in particular, for Russia in our sample— cause a decrease in volatility. The reverse effect on volatility is also reported by Li and Engle (1998) in a study of asymmetric effects of scheduled U.S. macroeconomic announcements on the treasury futures markets.

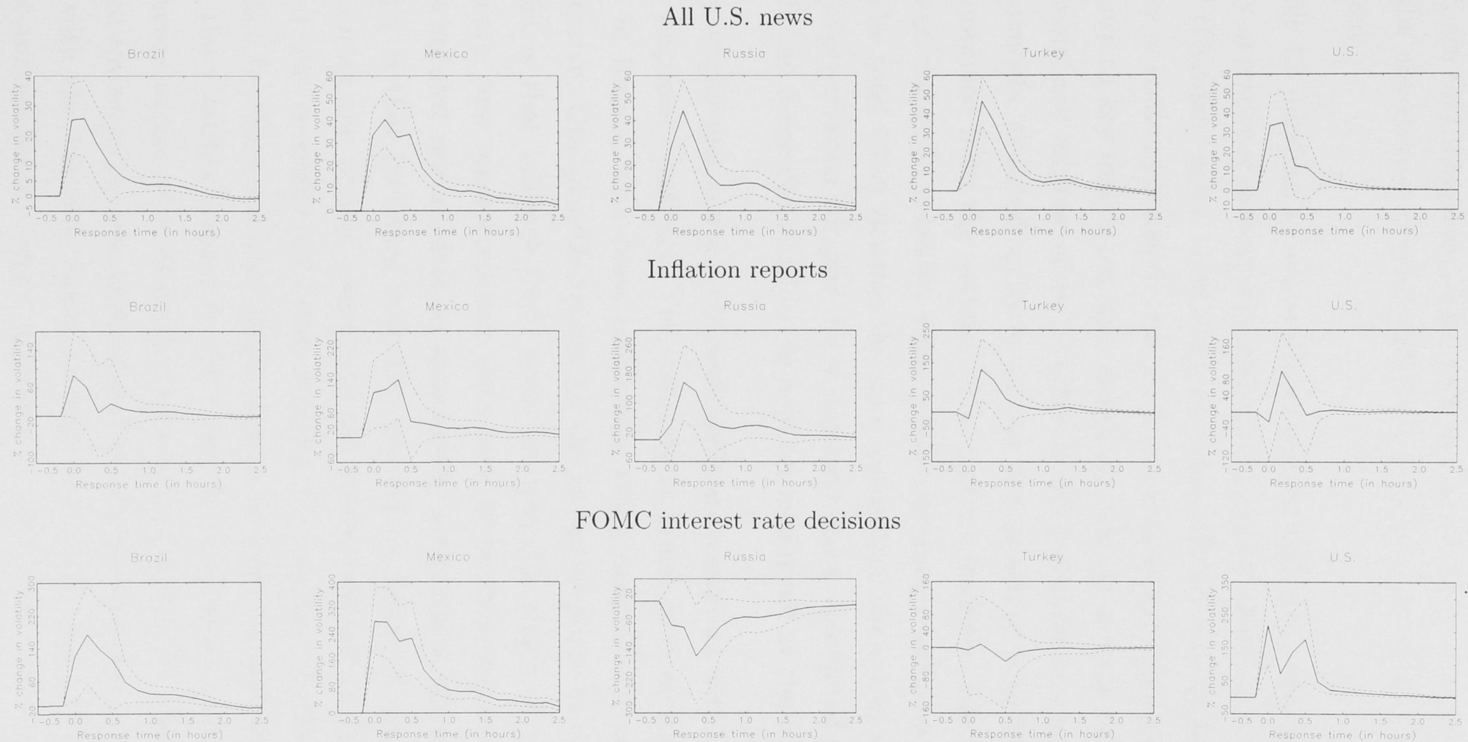
The pattern of markets' response to news is consistent across different types of indicators, for example, inflation releases. Federal Open Market Committee (FOMC) interest rate actions are uniformly inducing high volatility in U.S. dollar–denominated bonds of Brazil and Mexico, with volatility spiking two to three times higher in the first ten minutes, even though changes in the federal funds rate are perfectly predicted over the sample period and are known to be well anticipated by market participants in general (Bernanke and Kuttner, 2005). The response of Russia's and Turkey's euro-denominated

Figure 4.4: Volatility Response to Local News Arrival



Notes: The figures present the ten-minute volatility response to arrivals of all local macroeconomic news (top panel), inflation reports (centre panel) and policy interest rate decisions (bottom panel, with no meaningful monetary policy interest rates series available for Russia). The solid lines represent the median percentage change in volatility during the subprime crisis (the differences between the dynamics of the response before and during the crisis are negligible, and arise from small variations in the AR and ARCH parameters only) and the dashed lines represent the 95% confidence intervals. The estimates are obtained using Monte Carlo simulations based on parameter estimates reported in Table 4.5 and account for the estimation uncertainty. The x-axis denotes time *in hours*, with the announcements time fixed at 0. *Sample period:* October 1, 2006 – February 20, 2008. *Data sources:* Bloomberg, Tullett Prebon.

Figure 4.5: Volatility Response to U.S. News Arrival



Notes: The figures present the ten-minute volatility response to arrivals of all U.S. macroeconomic news (top panel), inflation reports (centre panel) and FOMC interest rate decisions (bottom panel). The solid lines represent the median percentage change in volatility during the subprime crisis (the differences between the dynamics of the response before and during the crisis are negligible, and arise from small variations in the AR and ARCH parameters only) and the dashed lines represent the 95% confidence intervals. The estimates are obtained using Monte Carlo simulations based on parameter estimates reported in Table 4.5 and account for the estimation uncertainty. The x-axis denotes time *in hours*, with the announcements time fixed at 0. *Sample period:* October 1, 2006 – February 20, 2008. *Data sources:* Bloomberg, Tullett Prebon.

bonds to the European Central Bank's interest rate changes is visible but less pronounced. By contrast, local interest rate changes have a large, albeit delayed, effect only on Brazil's external bond. Two caveats to this finding, however, are that monetary policy rate changes in Mexico were largely absent during the observation period, and, in Russia, interest rates are not a policy instrument.

Table 4.5 provides a cross-sectional comparison of the average increases in volatility in response to domestic, global (U.S.), and—for Russia and Turkey—regional (German) news, controlling for other effects. The table provides the estimates of contemporaneous and total (accumulative) volatility news effects in response to key macroeconomic indicators and on average to all domestic, international and regional news. Coefficients for less important macroeconomic announcements, as listed in Table 4.2, are not presented here for brevity, but can be obtained from the authors. The contemporaneous effect denotes the percentage change in volatility when a macroeconomic indicator k is released (β_{k0}). The total effect denotes the total percentage change in volatility over the entire observation window (forty minutes) and is calculated as $\sum_{j'=0}^{3} \beta_{kj'}$. All coefficient estimates provided in bold are significant at the 5 percent level.

The magnitudes and signs of coefficients are consistent with the illustrated impulse response functions. The volatility response to domestic news is the weakest in Russia, with most coefficients being insignificant and, at times, even negative. One possible reason for the muted response to domestic news in Russia is that releases there occur at irregular times of the day, and, furthermore, new macroeconomic data tend to be preannounced in advance of the scheduled release date in speeches by government officials. Another possibility is that investors were less focused on domestic data releases in Russia during the period covered by the study, because at that time they perceived the economy as being resilient to external shocks and having the ability to repay external debt, thanks to high oil and gas prices. In Turkey, the volatility impact is also found to be delayed, perhaps due to a simultaneous release of several macroeconomic indicators.[12] These two results show that investors process unscheduled and/or multiple news releases slowly, in line with the learning model of Kim and Verrecchia (1991a), in which the post-announcement return volatility is lower when announcements are

[12]To disentangle individual indicators' responses to releases, we use the surprise content of releases instead of the release times. We find that surprises in PPI tend to have a more immediate impact on volatility than surprises in CPI.

Table 4.5: Impact of News Arrival on Ten-minute Return Volatility

	Brazil		Mexico		Russia		Turkey		U.S.	
	ContEff	*TotEff*	*ContEff*	*TotEff*	*ContEff*	*TotEff*	*ContEff*	*TotEff*	*ContEff*	*TotEff*
All Domestic News	**46.11**	**51.69**	**38.281**	36.44	11.89	-10.29	-8.20	**56.70**		
GDP	**152.09**	214.70	73.35	83.78	-58.84	-34.04	-31.60	-81.19		
Trade Balance	37.61	41.90	40.98	-155.54	**-111.64**	-252.73	-37.09	15.59		
CPI	**165.19**	**236.41**	**124.19**	**185.53**	163.97	**614.42**	61.09	113.86		
Unemployment	**72.41**	13.80	**150.09**	17.87	24.88	-46.55	**136.24**	**177.7**		
Interest Rate	98.44	**466.52**	39.21	37.34			2.80	**116.16**		
All U.S. News	**25.54**	**49.88**	**33.70**	**92.89**	**27.59**	**62.21**	**15.89**	**77.87**	**33.123**	**68.91**
GDP	**136.08**	36.24	**156.45**	**423.09**	**140.63**	**294.15**	**133.55**	**183.62**	91.43	**161.05**
Trade Balance	39.00	85.82	5.09	146.37	18.10	89.94	1.55	-28.13	-16.98	-0.11
CPI	86.21	113.47	**108.66**	**239.68**	42.66	**202.24**	-20.27	**165.89**	-23.22	92.12
Unemployment	-5.49	55.71	25.76	38.02	20.60	16.39	**40.42**	**120.14**	21.51	83.10
Interest Rate	119.71	**361.92**	**279.94**	**645**	**-63.69**	**-238.14**	-5.77	-41.10	**218.51**	**506.45**
All German News					**48.76**	39.77	-8.79	-8.89		
GDP					**277.23**	-127.58	-18.68	41.00		
Trade Balance					**93.6**	**272.08**	**83.51**	-10.32		
CPI					45.11	70.46	36.36	38.28		
Unemployment					-19.42	**-257.94**	-74.55	-59.35		
Interest Rate					-61.94	-32.24	**88.54**	63.20		

(cont.)

Table 4.5: Impact of News Arrival on Ten-minute Return Volatility *(table notes)*

Notes: We estimate the news response model for emerging market external bonds and the ten-year U.S. treasury note:

$$\begin{aligned} R_t &= \beta_0 + \sum_{i=1}^{I} \beta_i R_{t-i} + \sum_{k=1}^{K} \beta_k S_{k,t} + \varepsilon_t, \\ \ln|\hat{\varepsilon}_t| &= \alpha + \phi(t) + \psi\sigma_{d(t)} + \sum_{i=1}^{I'} \beta_i \ln|\hat{\varepsilon}_{t-i}| + \sum_{k=1}^{K}\sum_{j'=0}^{3} \beta_{kj'} A_{k,t-j'} + \ln u_t, \end{aligned}$$

where R_t is the ten-minute log-return, $\sigma_{d(t)}$ is the long memory volatility over the day containing the return t, and $\phi(t)$ denotes a cubic spline that estimates the intradaily and weekly seasonality. $S_{k,t}$ is the standardized news corresponding to a macroeconomic fundamental k released at time t, $k = 1, \ldots, K$, and $A_{k,t}$ is a dummy variable indicating the release of this fundamental. I and I' denote the autoregressive (AR/ARCH) effects, as specified in Table 4.3. The average impact of domestic, U.S. and German news arrival on volatility is estimated within a summary model, where $A_{k,t}$ is included in both mean and volatility equations and denotes releases of grouped announcements: (a) domestic and U.S. for BZ40 and MX17 bonds, (b) domestic, U.S. and German for RU30 and TU30 bonds, and (c) U.S. only for U.S. ten-year Treasury note. *ContEff* denotes the percentage change in volatility when news occurs (β_{k0}). *TotEff* denotes the total percentage change in volatility over the observation window of 40 minutes, calculated as $\sum_{j'=0}^{3} \beta_{kj'}$ and tested for significance using the $\chi^2(4)$ Wald statistic. Coefficients provided in **bold** are significant at the 5% level, using heteroscedasticity- and autocorrelation-consistent standard errors. *Sample period:* October 1, 2006 – February 20, 2008. *Data sources:* Bloomberg, Tullett Prebon.

unanticipated or of uncertain quality. The magnitude of volatility effect in Turkey is larger compared to Russia, possibly reflecting investors' perceptions of Turkey's greater vulnerabilities. Unlike the markets for Russian and Turkish bonds, those for Brazilian and Mexican bonds react instantaneously and significantly to a gamut of domestic macroeconomic announcements.

Besides the country-specific factors discussed above, the relevance of macroeconomic information for investors is likely to depend on its general characteristics: timeliness,[13] marginal information content, and reliability. A careful analysis of all individual news coefficients[14] in relation to the news releases calendar suggests that indicators released on a more timely, frequent basis could be seen as more relevant. For example, by their much stronger response to weekly releases of trade balance data in Brazil than to monthly data releases and to preview CPI data in Brazil and Mexico than to later releases. However, in some cases, even those indicators that are released late could be highly relevant for markets. For example, despite being released late in the reporting cycle, GDP appears to have a large marginal information

[13]Chart 2 of Fleming and Remolona (1997) and Figure 2 of Andersen et al. (2003) show graphically the pattern of U.S. release dates throughout the month. We have also drafted similar charts for the releases in the emerging economies considered in our study. They provide a visual evidence of some redundancy and small surprise content of particular indicators, as discussed in this section.

[14]Individual news coefficients for all macroeconomic indicators considered in this study, as listed in Table 4.2, are no reported for brevity, but can be obtained from the author.

content for emerging markets, suggesting that investors' expectations are not well guided by releases of higher-frequency data, such as those on industrial production or retail sales. This contrasts with the United States, where Advance GDP[15] figures mirror earlier releases of monthly personal spending (consumption accounts for more than 70 percent of GDP in the United States). Jointly released personal income and spending indeed tend to induce significant volatility in emerging market and U.S. bonds. Hence, we do not find strong evidence that advance GDP consistently raises volatility. Yet Preliminary GDP (released one month later than advance GDP), which also includes foreign trade data and revisions, does raise volatility.

Perceived data reliability is also an important factor that determines market reaction. Some statistics could be subject to considerable error margins and frequent revisions, dampening market reaction to the original release. However, examining the role of data revisions is outside the scope of this study. In addition, the quality of analysts' forecasts has a bearing on the magnitude of surprises and hence market reaction. Providing early guidance to markets—through the publication of preliminary and advance figures, policy decision rules, and preannouncement of new data in official speeches or informal information leakage—would reduce the magnitude of surprises and market reaction.

4.6.3 Asymmetries and Nonlinearities

Finally, we test for the presence of asymmetries and nonlinearities in the process of information absorption in emerging bond markets: (*1*) Does bad news matter more than good news? (*2*) Do big surprises move markets more than small surprises? (*3*) Does macroeconomic news matter more during calm times or during financial turbulence, which, in our sample, follows the onset of the U.S. financial crisis?

Evidence from behavioural studies suggests that negative news tends to trigger a stronger response than positive news (see, for example, Gosnell et al., 1996; and Andersen et al., 2003). We test for asymmetric responses by regressing the return series on a set of dummy variables that are based on the direction of surprises. We then indicate releases of either positive or negative grouped announcements. We classify the fundamentals as either narrowly

[15]There are three successive "current quarterly" estimates of GDP in the U.S.: "Advance," "Preliminary," and "Final."

defined real activity statistics (GDP, industrial production, investment, and retail sales for local real activity; and GDP, industrial production, construction spending, personal consumption, personal spending, and retail sales for U.S. real activity) or inflation. In line with Bauwens et al. (2005b), we assume that if an announced figure for a real activity variable is larger than the market expectation and the variable contributes to economic growth, the news is classified as positive; otherwise, it is classified as negative. For inflation, if an announced figure implies lower inflation, the news is classified as positive; otherwise, it is classified as negative. The results are reported in Table 4.6.

In line with previous empirical studies, we find that negative local news produces more volatility over the total observation window than positive news. Also, negative U.S. real economic shocks met with a stronger response than did positive shocks, in particular, for Mexican, Turkish and U.S. bonds. In contrast, positive U.S. inflation news, which may be signalling an outlook for a tightening of monetary policy and a future depressing of U.S. bond prices, causes greater volatility in all bonds. This finding suggests that as emerging economies' bonds become more attractive investments (assuming that emerging economies' monetary policy remains unchanged), there is a significant increase in trading activity related to investors' repositioning their portfolios. Given the Mexican government's debt exchange program of peso bonds for U.S. dollar-denominated bonds, it is not surprising that this effect is most pronounced for the Mexican bond.

Rigobon and Sack (2006) suggest that noisiness and measurement problems explain why the estimated response of macroeconomic announcements on asset prices is rather small. We suspect that this is particularly true for small surprises that do not cause a shift in the macroeconomic outlook in which investors believe. However, large surprises may prompt investors to reconsider their views on the outlook and reshuffle their portfolios, triggering a larger increase in volatility. This hypothesis can be tested by classifying the standardized surprise into two categories (big and small surprises) by absolute magnitude. Judging by model fit, the optimal cutoff for our data lies between the 40 percent quantile (Brazil) and the 80 percent quantile (Mexico). We choose the 70 percent quantile to compare coefficients across countries and present the results in Table 4.7). Table 4.7 provides some evidence that larger surprises in the U.S. data trigger a more sizable and more immediate volatility reaction than large surprises in domestic news.

Table 4.6: Impact of Positive and Negative News Arrival on Ten-minute Return Volatility

	Brazil		Mexico		Russia		Turkey		U.S.	
	ContEff	*TotEff*	*ContEff*	*TotEff*	*ContEff*	*TotEff*	*ContEff*	*TotEff*	*ContEff*	*TotEff*
Domestic news										
Positive real activity news	64.38	-36.35	**79.03**	26.95	5.68	-68.73	62.02	185.72		
Negative real activity news	113.56	**185.22**	**41.53**	80.65	**117.3**	60.90	**157.73**	137.49		
Positive inflation news	**88.31**	**74.32**	**168.50**	115.20	14.50	-77.83	13.26	24.33		
Negative inflation news	**54.03**	**80.10**	**165.73**	112.23	90.46	69.08	42.83	125.01		
U.S. news										
Positive real activity news	9.34	57.64	1.71	55.69	1.47	**134.63**	-44.77	**83.59**	23.17	-9.47
Negative real activity news	37.45	30.50	34.96	**183.67**	3.89	74.77	-3.70	**141.47**	**52.62**	**172.95**
Positive inflation news	58.36	**179.03**	**103.68**	**390.86**	66.42	**193.9**	**53.29**	**231.97**	51.02	**171.95**
Negative inflation news	26.18	80.17	**99.78**	**180.58**	-23.15	-7.58	-31.48	43.53	-17.54	83.71

Notes: We estimate the news response model for emerging market external bonds and the ten-year U.S. treasury note:

$$
\begin{aligned}
R_t &= \beta_0 + \sum_{i=1}^{I} \beta_i R_{t-i} + \sum_{k \in news^{\diamond}} \beta_k A^*_{k,t} + \varepsilon_t, \\
\ln|\hat{\varepsilon}_t| &= \alpha + \phi(t) + \psi \sigma_{d(t)} + \sum_{i=1}^{I'} \beta_i \ln|\hat{\varepsilon}_{t-i}| + \sum_{k \in news^{\diamond}} \sum_{j'=0}^{3} \beta_{kj'} A^*_{k,t-j'} + \ln u_t,
\end{aligned}
$$

where R_t is the ten-minute log-return, $\sigma_{d(t)}$ is the long memory volatility over the day containing the return t, and $\phi(t)$ denotes a cubic spline that estimates the intradaily and weekly seasonality. I and I' denote the autoregressive (AR/ARCH) effects, as specified in Table 4.3. $A^*_{k,t}$ is a dummy variable indicating releases of positive or negative grouped announcements; local real activity (GDP, industrial production, investment, and retail sales) and inflation, and U.S. real activity (GDP, industrial production, construction spending, personal consumption, personal spending, and retail sales) and inflation. For real activity, if the announced macroeconomic figures are larger than the market expectations and the variable contributes to economic growth, the news is classified as positive, and negative otherwise. For inflation, if the announced figures imply less inflation, the news is classified as positive, and negative otherwise. *ContEff* denotes the percentage change in volatility when news occurs (β_{k0}). *TotEff* denotes the total percentage change in volatility over the observation window of 40 minutes, calculated as $\sum_{j'=0}^{3} \beta_{kj'}$ and tested for significance using the $\chi^2(4)$ Wald statistic. Coefficients provided in **bold** are significant at the 5% level, using heteroscedasticity- and autocorrelation-consistent standard errors. *Sample period:* October 1, 2006 – February 20, 2008. *Data sources:* Bloomberg, Tullett Prebon.

Table 4.7: Impact of Surprise News in the Upper and Lower 0.70 Quantile on Ten-minute Return Volatility

	Brazil		**Mexico**		**Russia**		**Turkey**		**U.S.**	
	ContEff	*TotEff*	*ContEff*	*TotEff*	*ContEff*	*TotEff*	*ContEff*	*TotEff*	*ContEff*	*TotEff*
Domestic news										
Lower quantile	**89.86**	**67.32**	**69.92**	**68.23**	17.71	45.67	**66.24**	**112.06**		
Upper quantile	**38.93**	**78.57**	**66.12**	21.52	69.74	-43.18	24.50	70.34		
U.S. news										
Lower quantile	8.05	**55.17**	-3.30	**72.46**	**33.13**	**69.14**	**26.68**	**106.26**	**34.53**	**95.04**
Upper quantile	**32.35**	**51.08**	**64.96**	**121.47**	**53.45**	**131.86**	**35.49**	**143.52**	**52.23**	**92.21**
German news										
Lower quantile					**117.64**	75.34	**66.92**	**89.57**		
Upper quantile					**56.34**	-17.06	**37.7**	-44.68		

Notes: We estimate the news response model for emerging market external bonds and the ten-year U.S. treasury note,

$$R_t = \beta_0 + \sum_{i=1}^{I} \beta_i R_{t-i} + \sum_{k \in news^*} \beta_k A^*_{k,t} + \varepsilon_t,$$

$$\ln|\hat{\varepsilon}_t| = \alpha + \phi(t) + \psi\sigma_{d(t)} + \sum_{i=1}^{I'} \beta_i \ln|\hat{\varepsilon}_{t-i}| + \sum_{k \in news^*} \sum_{j'=0}^{3} \beta_{kj'} A^*_{k,t-j'} + \ln u_t,$$

where R_t is the ten-minute log-return, $\sigma_{d(t)}$ is the long memory volatility over the day containing the return t, and $\phi(t)$ denotes a cubic spline that estimates the intradaily and weekly seasonality. I and I' denote the autoregressive (AR/ARCH) effects, as specified in Table 4.3. $A^*_{k,t}$ is a dummy variable indicating releases of grouped announcements: (1) domestic and U.S. for BZ40 and MX17 bonds, (2) domestic, U.S., and German for RU30 and TU30 bonds, and (3) U.S. only for the U.S. treasury note. For each group of announcements, we classifying the standardized surprise into two categories by absolute magnitude, with surprises in the lower 0.7 quantile defined as "small," and the others defined as "large." *ContEff* denotes the percentage change in volatility when news occurs (β_{k0}). *TotEff* denotes the total percentage change in volatility over the observation window of 40 minutes, calculated as $\sum_{j'=0}^{3} \beta_{kj'}$ and tested for significance using the $\chi^2(4)$ Wald statistic. Coefficients provided in **bold** are significant at the 5% level, using heteroscedasticity- and autocorrelation-consistent standard errors. *Sample period:* October 1, 2006 – February 20, 2008. *Data sources:* Bloomberg, Tullett Prebon.

The last part of our analysis focuses on the differences in response to domestic and international macroeconomic releases since the onset of the onset of financial turbulence in June 2007. These results are reported in Table 4.8. We find that the response to U.S. macroeconomic releases has become less pronounced, with domestic news in Brazil and Turkey gaining in importance. Although intraday volatility has increased, the aggregate effect of U.S. surprises on volatility in emerging bond markets has become less consistent and weaker during financial turbulence. The shift in attention away from broad aggregate indicators toward specific and more timely indicators is consistent with the findings in Andritzky et al. (2007) for periods of emerging market crises. The striking decline in importance of U.S. macroeconomic news could also be viewed as indirect evidence of the perception of divergent growth dynamics in emerging economies and the United States during the period covered by the study. Given that during the crisis period covered by this story investors' attention was focussed exclusively on subprime losses, this effect might have reversed recently as the global growth implications have become clearer. According to market observers, during the early stage of the crisis bonds of higher-income emerging economies have served as a safe haven for investors during turbulence in mature financial markets.

4.7 Conclusion

This study is among the first to provide systematic evidence of the volatility dynamics of emerging bond markets and the role of macroeconomic fundamentals in the price discovery process in these markets.

An analysis of intraday data for selected external emerging market bonds suggests that the immediate price response to macroeconomic announcements is similar to that in mature markets in that it is nearly instantaneous. News is absorbed within a five-minute period. Like mature markets, this re-pricing process is accompanied by a prolonged period of elevated trading activity as investors reposition their portfolios. However, for emerging market bonds this process is more drawn-out. Volatility remains elevated for more than two hours after announcements—about twice as long as in mature bond markets—possibly owing to greater information asymmetries and lower liquidity in emerging markets. Even though overall volatility is consistently higher in emerging bond markets, these effects are clearly identified, while the intraday

Table 4.8: Impact of News Arrival on Ten-minute Return Volatility Before and During the Subprime Crisis

	Brazil		**Mexico**		**Russia**		**Turkey**		**U.S.**	
	ContEff	*TotEff*	*ContEff*	*TotEff*	*ContEff*	*TotEff*	*ContEff*	*TotEff*	*ContEff*	*TotEff*
Domestic news										
Before crisis	-7.50	27.12	**43.17**	29.37	**21.42**	-12.52	**28.03**	**61.98**		
During crisis	**45.12**	**56.05**	23.34	38.67	8.39	-11.52	**55.76**	**83.54**		
U.S. news										
Before crisis	**47.18**	**90.68**	**46.42**	**139.84**	**41.54**	**81.37**	**14.84**	**91.15**	**26.43**	**88.94**
During crisis	5.90	7.09	**20.03**	**44.94**	**18.02**	**33.64**	**19.78**	**67.74**	**17.3**	**41.18**
German news										
Before crisis					**92.59**	**94.44**	-19.82	-5.56		
During crisis					**28.46**	10.18	**33.96**	-12.82		

Notes: We estimate the average news response model for emerging market external bonds and the ten-year U.S. treasury note,

$$R_t = \beta_0 + \sum_{i=1}^{I} \beta_i R_{t-i} + \sum_{k \in news^{\dagger}} \beta_k A_{k,t} + \varepsilon_t,$$

$$\ln|\hat{\varepsilon}_t| = \alpha + \phi(t) + \psi\sigma_{d(t)} + \sum_{i=1}^{I'} \beta_i \ln|\hat{\varepsilon}_{t-i}| + \sum_{k \in news^{\dagger}} \sum_{j'=0}^{3} \beta_{kj'} A_{k,t-j'} + \ln u_t,$$

where R_t is the ten-minute log-return, $\sigma_{d(t)}$ is the long memory volatility over the day containing the return t, and $\phi(t)$ denotes a cubic spline that estimates the intradaily and weekly seasonality. I and I' denote the autoregressive (AR/ARCH) effects, as specified in Table 4.3. $A_{k,t}$ is a dummy variable indicating releases of grouped announcements: (1) domestic and U.S. for BZ40 and MX17 bonds, (2) domestic, U.S., and German for RU30 and TU30 bonds, and (3) U.S. only for the U.S. treasury note. *ContEff* denotes percentage change in volatility when news occurs (β_{k0}). *TotEff* denotes the total impact percentage change in volatility over the window of 40 minutes, calculated as $\sum_{j'=0}^{3} \beta_{kj'}$ and tested for significance using the χ^2 Wald statistic. Coefficients provided in **bold** are significant at the 5% level, using heteroscedasticity- and autocorrelation-consistent standard errors. *Sample period before crisis:* October 1, 2006 – June 4, 2007. *Sample period during crisis:* June 5, 2007 – February 20, 2008. *Data sources:* Bloomberg, Tullett Prebon.

volatility pattern during the core trading hours shows similar features as in mature foreign exchange markets. Altogether, this evidence lends support to the notion that preannounced macroeconomic releases offer a window of opportunity for trading, which plays an important role in less liquid markets.

We do not find evidence that a simultaneous release of several macroeconomic indicators triggers a more pronounced volatility response than do separate releases of individual indicators, although evidence from Turkey suggests that joint releases cause a delayed response. However, it appears that market reaction weakens when indicators are released at random times during the day or do not follow a preannounced release schedule. Furthermore, we find some anecdotal evidence for the role of timeliness, marginal information content, and reliability of both data and expectation measures.

International and regional news tends to be at least as important as local news, confirming close links between emerging and mature markets and the importance of global macroeconomic fundamentals for the performance of foreign currency-denominated emerging market assets. Such systemic "news spillovers," characterized by a homogeneous pattern of responses across all emerging market bonds in the study, seem to be less pronounced in the U.S. treasury market, which tends to be driven mostly by U.S. data releases. In particular, the volatility effect of announcements related to inflation and monetary policy in the U.S. are more likely to overwhelm any local news. We also confirm strong asymmetric effects of good versus bad news, which are often observed in mature markets, and we find that U.S. macroeconomic data releases that contain large surprises have a disproportionately large impact.

Finally, we find that in the wake of the U.S. financial crisis, investors in emerging market bonds have become more uncertain about the accuracy of macroeconomic news and shifted their attention away from releases of U.S. (and German) news, possibly based on the view that macroeconomic developments in the United States (and other mature market countries) have been driven by idiosyncratic factors. Despite a higher level of volatility and a significant increase in the number of quotes, we do not identify a general change in response patterns.

Chapter 5

Conclusions and Directions for Further Research

This thesis presents three related essays on the dynamic properties of the frequency of trading, price discovery, and intraday volatility, and the short-run impact of news arrival on the intraday behaviour of financial markets. The empirical investigation is conducted using high-frequency financial data for airline stocks, sampled at one-second intervals, and for emerging and mature bond market bond, sampled at one-minute and ten-minute intervals. This chapter summarizes the most important results and the original contributions of this thesis, and offers directions for future research.

5.1 Contributions of the Thesis

The first key contribution of this thesis is the focus on the frequency of trading in the financial markets, as measured by the conditional probability of trade in a given time interval. The analyses in chapters 2 and 3 explain the intraday dynamics in trading frequencies and the response to the information events. Trading frequency plays an important role in shaping the dynamics of financial markets, as it determines the speed at which financial markets respond to an announcement and the length of any response. However, the impact of information arrival on the frequency of trading has been largely neglected in the empirical literature. This study differs from others that look at microstructure effects on stocks by directly modeling the trading intensity and by estimating the conditional probability of trade in the next time interval.

Chapters 2 and 3 reveal that trading frequency is a long memory process characterized by positive, highly significant, and very persistent dynamic dependencies. It exhibits a U-shaped pattern over the course of the day, that is also characteristic for volatility, trade volumes, and bid/ask spreads. On average, trades in stocks are about twice as likely to occur during the opening auction and immediately prior to the market's close than during lunch-time.

The main result reported in chapter 2 is that on average, trading intensity in airlines stocks increases prior and consequent to macroeconomic announcements, but decreases around firm-specific releases. Market microstructure variables have a small yet significant effect on trading frequency, with high trade volume and narrow bid/ask spread inducing higher trading intensity. The negative impact of high trade volume on the conditional probability of trade is consistent with the seminal theoretical model of Easley and O'Hara (1992). However, the finding that trades are more likely to occur as the bid/ask spread narrows is in contrast to their predictions, though is supported by the Admati and Pfleiderer (1988) model.

Further, chapter 2 provides strong evidence that the intraday crude oil futures returns are relevant for modelling the probability of a trade in airline stocks within the next time period. This result confirms those of Sadorsky (1999) and Papapetrou (2001), who find that crude oil price movements are important in modelling monthly equity returns. We find that as crude oil futures prices rise, the conditional probability of a trade in airline stocks within the next time period significantly increases, with an exception of an airline renowned for a successful jet-fuel hedging program.

The second major contribution of this thesis is that it develops and extends a new econometric model called autoregressive conditional hazard (ACH) model, and evaluates its performance in both the in-sample and out-of-sample environments. The ACH model, first introduced by Hamilton and Jordà (2002), relates the conditional probability of trade, called the *hazard rate*, to the past observed and expected trade durations. Easley and O'Hara (1992) show that trade durations—the irregularly spaced waiting times between two consecutive trades—often convey information about the news flow to market participants. The ACH model allows one to analyse the informational content of tick-by-tick financial durations and other microstructure variables is a framework that is equally-spaced. Thus it provides a convenient way of analysing the impact of covariates that may change between trades, and it also facilitates the calculation of impulse response functions, and the estimation of multivariate models to study short-run spillovers between assets and between markets.

The analysis of chapter 2 demonstrates, in line with the findings of Demiralp and Jordà (2001), Hamilton and Jordà (2002), and Andersen et al. (2007b), that the ACH framework allows for efficient and flexible modelling of the in-sample conditional probabilities. However, time-series models tend to be evaluated according to their out-of-sample forecast performance (Anderson and Vahid, 2001). Thus the focus of chapter 3 is on the forecasting properties of the ACH model in the context of predicting the conditional probability of a trade occurring within the next time interval. This is perhaps the first study in the ACH literature to examine the ability of the ACH model to predict out of sample. The evaluation is conducted on a high-frequency financial dataset which entails an out-of-sample environment big enough to conduct meaningful statistical tests.

Chapter 3 demonstrates that the ACH model provides accurate probability forecasts, as evaluated using the quadratic and logarithmic scoring rules and the new tests of probability forecast encompassing developed by Clements and Harvey (2006). An application to airlines trade data shows that the most accurate individual forecasts are generated by a newly-developed ACH model that includes a measure of the length of time passed since the last observed trade (i.e. a no-trade duration). In contrast, the application of more complex specifications results in less accurate predictions. Forecasting accuracy is further improved by the means of Kamstra-Kennedy forecast combinations (Kamstra and Kennedy, 1998). This is consistent with previous findings about point forecasts; in general combined forecasts outperform the constituent forecasts.

The third important contribution of this work is that it uses very broad and often novel financial, announcements, and information datasets. In chapters 2 and 3, the empirical investigation into the intraday dynamics of trading frequency is conducted using high-frequency transaction and order data for three American airline equities traded on the New York Stock Exchange (NYSE). The airline data provides a interesting opportunity for jointly modelling the frequency of trading, market informational efficiency, and trading spillovers from the crude oil futures markets. To the best of our knowledge, this is the first empirical study based on high-frequency airline equity data, in contrast to numerous studies that investigate intraday behaviour of either a single stock (IBM) or the constituents of the Dow Jones Industrial Average.

The information dataset in chapter 2 not only consists of a standard set of real-time United States (U.S.) government announcements; it also includes scheduled and unscheduled company news published by Dow Jones Business News and PR Newswire. This is an important contribution to the debate on the role of information on the intraday price formation process, given that most research concentrates on response to scheduled macroeconomic releases only. We show that macroeconomic statistical releases increase the frequency of trading in stocks, in line the Easley and O'Hara (1992) model, but firm-specific announcements tend to have an opposite effect, in particular unscheduled airline security releases and other bad news. By comparison, good news such as favourable analysts' reports tend to increase the conditional probability of trade.

This announcement set is further supplemented by the New York Mercantile Exchange (NYMEX) intraday crude oil futures price data. This allows us to study how airline stocks, crude oil futures prices, and news arrival interact. This approach also facilitates an innovative investigation of the informational efficiency of crude oil futures prices that provide a single, readily quantifiable information source about a major component of U.S. passenger airline operating costs (ATA, 2006). Our results clearly indicate that tick-by-tick crude oil futures returns are highly relevant for modelling the probability of trade within the next time period.

Finally, the analysis in chapter 4 is based on a dataset of high-frequency emerging bond market returns and implements detailed datasets of macroeconomic releases and market expectations for four emerging and two developed economies. This essay is among the first to provide systematic evidence of the high-frequency volatility dynamics of emerging bond markets and the role of domestic and international macroeconomic fundamentals in the price discovery and trading activity processes in these markets. We show that as in mature markets, macroeconomic surprises in emerging bond markets affect both price discovery and volatility, with the effects on volatility being more pronounced and longer lasting than those on prices. The process of information absorption tends to be more drawn out in the emerging bond market than in the mature bond markets. Moreover, we observe systematic "news spillovers," with international news being at least as important as local news.

5.2 Future Extensions

Chapter 3 includes three suggested extensions to the ACH model. Firstly, an interesting direction for future research would be to extend the ACH model so that it can account for nonlinearities and asymmetry in the response of stock prices to information (asymmetries in adjusting to good/bad news are reported for example by Gosnell et al., 1996, in their study of dividend announcements). A smooth transition ACH framework could be developed for this purpose, in line with the research work of Teräsvirta and Anderson (1992), Anderson and Vahid (1998, 2001) and Anderson et al. (1999). Further extensions of the model could also involve price and/or volume durations instead of trade durations, and semiparametric and nonparametric estimation techniques, as in the closely related framework of Gerhard and Hautsch (2001).

Our results in chapters 2 and 3 demonstrate that high frequency crude oil futures return data is a very useful continuous-time information variable that is highly relevant for in-sample modelling and out-of-sample forecasting of the probability of trade in a given time interval. Drawing on the current findings, it seams justifiable to hypothesize that there is a future potential for using crude oil futures prices as a general proxy for information in other contexts. In particular, the crude oil futures prices should effectively incorporate information relevant for modelling the intraday behaviour of car and energy industries. Additional insights would come from assessing empirically whether the effectiveness of crude oil prices as a continuous information measure extends to the economy as a whole. We leave these issues for future research.

Bibliography

ABC News (2005). Oil Price Hits High after Hurricane Katrina [INTERNET]. *ABC News Online,* 31 August. Available from: `http://www.abc.net.au/news`.

Adams, G., McQueen, G., and Wood, R. (2004). The Effects of Inflation News on High Frequency Stock Returns. *Journal of Business*, 77(3):547–574.

Admati, A. R. and Pfleiderer, P. (1988). A Theory of Intraday Patterns: Volume and Price Variability. *Review of Financial Studies*, 1(1):3–40.

Albuquerque, R. A. and Vega, C. (2006). Asymmetric Information in the Stock Market: Economic News and Co-Movement. Discussion Paper 5598, Centre for Economic Policy Research.

Almeida, A., Goodhart, C., and Payne, R. (1998). The Effects of Macroeconomic News on High Frequency Exchange Rate Behavior. *Journal of Financial and Quantitative Analysis*, 33(3):383–408.

Andersen, T. G. and Bollerslev, T. (1997a). Heterogeneous Information Arrivals and Return Volatility Dynamics: Uncovering the Long-Run in High Frequency Returns. *Journal of Finance*, 52(3):975–1005.

Andersen, T. G. and Bollerslev, T. (1997b). Intraday Periodicity and Volatility Persistence in Financial Markets. *Journal of Empirical Finance*, 4:115–158.

Andersen, T. G. and Bollerslev, T. (1998). Deutsche MarkDollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies. *Journal of Finance*, 53(1):219–265.

Andersen, T. G., Bollerslev, T., and Cai, J. (2000). Intraday and Interday Volatility in the Japanese Stock Market. *Journal of International Financial Markets, Institutions and Money*, 10:107–130.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Ebens, H. (2001). The Distribution of Realized Stock Return Volatility. *Journal of Financial Economics*, 61(1):43–76.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Vega, C. (2003). Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange. *American Economic Review*, 93(1):38–62.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Vega, C. (2007a). Real-time Price Discovery in Global Stock, Bond and Foreign Exchange Markets. *Journal of International Economics*, 73:251–277.

Andersen, T. G., Bollerslev, T., and Huang, X. (2007b). A Reduced Form Framework for Modeling Volatility of Speculative Prices based on Realized Variation Measures. Working paper, Duke University.

Anderson, H. M., Nam, K., and Vahid, F. (1999). Asymmetric Nonlinear Smooth Transition GARCH Models. In Rothman, P., editor, *Nonlinear Time Series Analysis of Economic and Financial Data*. Boston: Kluwer Academic Press.

Anderson, H. M. and Vahid, F. (1998). Testing Multiple Equation Systems for Common Nonlinear Components. *Journal of Econometrics*, 84(1):1–36.

Anderson, H. M. and Vahid, F. (2001). Market Architecture and Nonlinear Dynamics of Australian Stock and Futures Indices. *Australian Economic Papers*, 40(4):541–566.

Andersson, M. (2007). Using Intraday Data to Gauge Financial Market Responses to Fed and ECB Monetary Policy Decisions. Working Paper 726, European Central Bank.

Andritzky, J. R., Bannister, G. J., and Tamirisa, N. T. (2007). The Impact of Macroeconomic Announcements on Emerging Market Bonds. *Emerging Markets Review*, 8:20–37.

ATA (2006). Air Transport Association of America website [INTERNET]. Available from: `http://www.airlines.org`.

Baillie, R. T. and Bollerslev, T. (1989). The Message in Daily Exchange Rates: A Conditional Variance Tale. *Journal of Business and Economic Statistics*, 7:297–305.

Balduzzi, P., Elton, E. J., and Green, C. (2001). Economic News and Bond Prices: Evidence from the U.S. Treasury Market. *Journal of Financial and Quantitative Analysis*, 36(4):523–543.

Balke, N. S., Brown, S. P. A., and Yücel, M. (1998). Crude Oil and Gasoline Prices: an Asymmetric Relationship? *Economic and Financial Policy Review*, Q 1:2–11.

Bauwens, L. and Giot, P. (1998). Asymmetric ACD Models: Introducing Price Information in ACD models with a Two State Transition Model. CORE Discussion Paper 9844, Université Catholique de Louvain, Louvain-La-Neuve.

Bauwens, L. and Giot, P. (2000). The Logarithmic ACD Model: An Application to the Bid-Ask Quote Process of Three NYSE Stocks. *Annales d'Économie et de Statistique*, 60:117–149.

Bauwens, L., Giot, P., Grammig, J., and Veredas, D. (2005a). A Comparison of Financial Duration Models via Density Forecasts. *International Journal of Forecasting*, 20(4):589–609.

Bauwens, L., Omrane, W. B., and Giot, P. (2005b). News Announcements, Market Activity and Volatility in the Euro/Dollar Foreign Exchange Market. *Journal of International Money and Finance*, 24:1108–1125.

Bauwens, L. and Veredas, D. (1999). The Stochastic Conditional Duration Model: A Latent Factor Model for the Analysis of Financial Durations.

CORE Discussion Paper 9958, Université Catholique de Louvain, Louvain-La-Neuve.

BEA (2006). U.S. Bureau of Economic Analysis website [INTERNET]. Available from: `http://www.bea.gov`.

Bernanke, B. S. and Kuttner, K. N. (2005). What Explains the Stock Market's Reaction to Federal Reserve Policy? *Journal of Finance*, 60(3):1221–1257.

Biais, B., Glosten, L., and Spatt, C. (2005). Market Microstructure: A Survey of Microfoundations, Empirical Results, and Policy Implications. *Journal of Financial Markets*, 8(2):217–264.

Blume, M. E. and Goldstein, M. A. (1997). Quotes, Order Flow, and Price Discovery. *Journal of Finance*, 52(1):221–244.

Boehmer, E., Saar, G., and Yu, L. (2005). Lifting the Veil: An Analysis of Pre-trade Transparency at the NYSE. *Journal of Finance*, 60(2):783–815.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, 31(3):307–327.

Bollerslev, T. (2001). Financial Econometrics: Past Developments and Future Challenges. *Journal of Econometrics*, 100:41–51.

Bollerslev, T., Cai, J., and Song, F. M. (2000). Intraday Periodicity, Long Memory Volatility, and Macroeconomic Announcement Effects in the U.S. Treasury Bond Market. *Journal of Empirical Finance*, 37:37–55.

Bollerslev, T. and Domowitz, I. (1993). Trading Patterns and Prices in the Interbank Foreign Exchange Market. *Journal of Finance*, 48(4):1421–1443.

Brier, G. W. (1950). Verification of Forecasts Expressed in Terms of Probability. *Monthly Weather Review*, 75:1–3.

Brooks, R. M., Patel, A., and Su, T. (2003). How the Equity Market Responds to Unanticipated Events. *Journal of Business*, 76(1):109–133.

Burbidge, J. and Harrison, A. (1984). Testing for the Effects of Oil-Price Rises using Vector Autoregressions. *International Economic Review*, 25(2):459–484.

Carroll, C. D., Fuhrer, J. C., and Wilcox, D. W. (1994). Does Consumer Sentiment Forecast Household Spending? If So, Why? *American Economic Review*, 84(5):1397–1408.

Chang, Y. and Taylor, S. J. (1998). Intraday Effects of Foreign Exchange Intervention by the Bank of Japan. *Journal of International Money and Finance*, 17:191–210.

Chang, Y. and Taylor, S. J. (2003). Information Arrivals and Intraday Exchange Rate Volatility. *Journal of International Financial Markets, Institutions and Money*, 13:85–112.

Clemen, R. T. (1989). Combining Forecasts: A Review and Annotated Bibliography. *International Journal of Forecasting*, 5:559–581.

Clements, M. P. and Harvey, D. I. (2006). Forecast Encompassing Tests and Probability Forecasts. Warwick Economic Research Paper 774, University of Warwick.

Clements, M. P. and Harvey, D. I. (2007). Combining Probability Forecasts. Working paper, University of Warwick.

Cox, J. (2005). The High Cost of Aviation Fuel [INTERNET]. Available from: `http://www.globalair.com`.

Cutler, D. M., Poterba, J. M., and Summers, L. H. (1989). What Moves Stock Prices? *Journal of Portfolio Management*, 15(3):4–12.

Dacarogna, M. M., Gençay, R., Müller, U. A., Olsen, R. B., and Pictet, O. V. (2001). *An Introduction to High-Frequency Finance*. Academic Press, An Imprint of Elsevier.

Damodaran, A. (1989). The Weekend Effect in Information Releases: a Study of Earnings and Dividend Announcements. *Review of Financial Studies*, 2(4):607–623.

Daníelsson, J. and Payne, R. (2002). Real Trading Patterns and Prices in Spot Foreign Exchange Markets. *Journal of International Money and Finance*, 21:203–222.

De Boor, C. (1978). *A Practical Guide to Splines*. New York: Springer-Verlag.

DeGennaro, R. P. and Shrieves, R. E. (1997). Public Information Releases, Private Information Arrival and Volatility in the Foreign Exchange Market. *Journal of Empirical Finance*, 4(4):295–315.

Demiralp, S. and Jordà, O. (2001). The Pavlovian Response of Term Rates to Fed Announcements. Finance and Economics Discussion Series 2001–10, Board of Governors of the Federal Reserve System.

Diamond, D. W. and Verrecchia, R. E. (1987). Constraints on Short-selling and Asset Price Adjustment to Private Information. *Journal of Financial Economics*, 18(2):277–311.

Diebold, F. X. and Lopez, J. A. (1996). Forecast Evaluation and Combination. In Maddala, G. S. and Rao, C. R., editors, *Handbook of Statistics*, volume 14, pages 241–268. Amsterdam: North-Holland.

Diebold, F. X. and Mariano, R. S. (1995). Comparing Predictive Accuracy. *Journal of Business and Economic Statistics*, 13(3):253–263.

Diebold, F. X. and Rudebusch, G. D. (1998). Scoring the Leading Indicators. *Journal of Business*, 62:369–391.

Dominguez, K. M. (2006). When Do Central Bank Interventions Influence Intra-daily and Longer-term Exchange Rate Movements? *Journal of International Money and Finance*, 25(7):1051–1071.

Dow, J. (2005). Is Liquidity Self-Fulfilling? *Journal of Business*, 77:895–908.

DRI-WEFA, Inc. (2002). The National Economic Impact of Civil Aviation. Unpublished report, Waltham, Massachusetts.

Dufour, A. and Engle, R. F. (2000a). The ACD Model: Predictability of the Time Between Consecutive Trades. Discussion Paper in Finance 2000-05, ISMA Centre, University of Reading.

Dufour, A. and Engle, R. F. (2000b). Time and the Price Impact of a Trade. *Journal of Finance*, 55(6):2467–2498.

Dungey, M., Fakhrutdinova, L., and Goodhart, C. (2008a). After Hours Trading in the Electronic Futures Markets. *Journal of Futures Markets*, 29(2):114–136.

Dungey, M., Henry, O., and McKenzie, M. (2008b). From Trade-to-Trade in US Treasuries: Durations, Workups and News Effects. unpublished manuscript.

Dwyer, G. P. and Hafer, R. (1989). Interest Rates and Economic Announcements. *Review,* Federal Reserve Bank of St. Louis, 48:34–46.

Easley, D., Kiefer, N. M., O'Hara, M., and Paperman, J. B. (1996). Liquidity, Information, and Infrequently Traded Stocks. *Journal of Finance*, 51(4):1405–1436.

Easley, D. and O'Hara, M. (1987). Price, Trade Size, and Information in Securities Markets. *Journal of Financial Economics*, 19(1):69–90.

Easley, D. and O'Hara, M. (1992). Time and the Process of Security Price Adjustment. *Journal of Finance*, 47(2):577–605.

Ederington, L. H. and Lee, J. H. (1993). How Markets Process Information: News Releases and Volatility. *Journal of Finance*, 48(4):1161–1191.

Ederington, L. H. and Lee, J. H. (1995). The Short-Run Dynamics of the Price Adjustment to New Information. *Journal of Financial and Quantitative Analysis*, 30(1):117–134.

Ederington, L. H. and Lee, J. H. (2001). Intraday Volatility in Interest-Rate and Foreign-Exchange Markets: ARCH, Announcements, and Seasonality Effects. *Journal of Futures Markets*, 21(6):517–552.

EIA (2006). Energy Information Administration. Official Energy Statistics from the U.S. Government [INTERNET]. Available from: `http://www.eia.doe.gov`.

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50(4):987–1008.

Engle, R. F. (2000). The Econometrics of Ultra-High-Frequency Data. *Econometrica*, 68(1):1–22.

Engle, R. F. and Patton, A. J. (2004). Impact of Trades in an Error-Correction Model of Quote Prices. *Journal of Financial Markets*, 7(1):1–25.

Engle, R. F. and Russell, J. R. (1995). Autoregressive Conditional Duration: A New Model for Irregularly Spaced Time Series Data. Economics Working Paper Series 94–27r, Department of Economics, University of California at San Diego.

Engle, R. F. and Russell, J. R. (1997). Forecasting the Frequency of Changes in Quoted Foreign Exchange Prices with the ACD Model. *Journal of Empirical Finance*, 4(2–3):187–212.

Engle, R. F. and Russell, J. R. (1998). Autoregressive Conditional Duration: A New Model for Irregularly Spaced Transaction Data. *Econometrica*, 66(5):1127–1162.

Eubank, R. L. (1988). *Spline Smoothing and Nonparametric Regression*, volume 90 of *Statistics, Textbooks and Monographs*. New York: Marcel Dekker.

Evans, G. (2006). Crude Oil Rises From One-Week Low as Lebanon Conflict Continues [INTERNET]. *Bloomberg*, 18 July. Available from: `http://www.bloomberg.com`.

Fama, E. F., Fisher, L., Jensen, M. C., and Roll, R. (1969). The Adjustment of Stock Prices to New Information. *International Economic Review*, 10(1):1–21.

Fernandes, M. and Grammig, J. (2006). A Family of Autoregressive Conditional Duration Models. *Journal of Econometrics*, 130(1):1–23.

Fleming, M. J. and Remolona, E. M. (1997). What Moves the Bond Market? Economic Policy Review 3(4), Federal Reserve Bank of New York.

Fleming, M. J. and Remolona, E. M. (1999). Price Formation and Liquidity in the U.S. Treasury Market: The Response to Public Information. *Journal of Finance*, 54(5):1901–1915.

Forsberg, L. and Ghysels, E. (2007). Why Do Absolute Returns Predict Volatility So Well? *Journal of Financial Econometrics*, 5:31–67.

Gau, Y.-F. and Hua, M. (2007). Intraday Exchange Rate Volatility: ARCH, News and Seasonality Effects. *Quarterly Review of Economics and Finance*, 13:135–158.

Gerhard, F. and Hautsch, N. (2001). Semiparametric Autoregressive Conditional Proportional Hazard Models. Nuffield College, Economics Working Paper W2, Nuffield College, University of Oxford.

Geweke, J. (1986). Modelling the Persistence of Conditional Variances: A Comment. *Econometric Reviews*, 5:57–61.

Ghysels, E., Gouriéroux, C., and Jasiak, J. (2004). Stochastic Volatility Duration Models. *Journal of Econometrics*, 119:413–433.

Gisser, M. and Goodwin, T. H. (1986). Crude Oil and the Macroeconomy: Tests of Some Popular Notions: Note. *Journal of Money, Credit and Banking*, 18(1):95–103.

Goldman Sachs (2008). Understanding US Economic Statistics, Sixth Edition.

Goodhart, C., Ito, T., and Payne, R. (1996). One Day in June, 1993: A Study of the Workings of Reuters D2000-2 Electronic Foreign Exchange Trading System. In Frankel, J., Galli, G., and Giovannini, A., editors, *The Microstructure of Foreign Exchange Markets*, pages 107–179. Chicago: University of Chicago Press.

Goodhart, C. A. E. and O'Hara, M. (1997). High Frequency Data in Financial Markets: Issues and Applications. *Journal of Empirical Finance*, 4(2-3).

Gosnell, T. F., Keown, A. J., and Pinkerton, J. M. (1996). The Intraday Speed of Stock Price Adjustment to Major Dividend Changes: Bid-Ask Bounce and Order Flow Imbalances. *Journal of Banking and Finance*, 20(2):247–266.

Green, C. T. (2004). Economic News and the Impact of Trading on Bond Prices. *Journal of Finance*, 54(3):1201–1233.

Greene, J. T. and Watts, S. G. (1996). Price Discovery on the NYSE and the NASDAQ: The Case of Overnight and Daytime News Releases. *Financial Management*, 25(1):19–42.

Guillaume, D. M., Dacorogna, M. M., Davé, R. R., Müller, U. A., Olsen, R. B., and Pictet, O. V. (1997). From the Bird's Eye to the Microscope: A Survey of New Stylized Facts of the Intra-daily Foreign Exchange Markets. *Finance and Stochastics*, 1(2):95–129.

Gulley, D. O. and Sultan, J. (1998). Consumer Confidence Announcements: Do They Matter? *Applied Financial Economics*, 8(2):155–166.

Gunn, L. D. (2007). *The Effect of Firm Specific Announcements on Banking Stocks on the Australian Stock Exchange*. PhD thesis, Department of Economics and Business Statistics, Faculty of Business and Economics, Monash University.

Hakkio, C. S. and Pearce, D. K. (1985). The Reaction of Exchange Rates to Economic News. *Economic Inquiry*, 23(4):621–636.

Hamilton, J. D. (1983). Oil and the Macroeconomy since World War II. *Journal of Political Economy*, 91(2):228–248.

Hamilton, J. D. (1989). A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. *Econometrica*, 57:357–384.

Hamilton, J. D. (1996). This is What Happened to the Oil Price-Macroeconomy Relationship. *Journal of Monetary Economics*, 38(2):215–220.

Hamilton, J. D. (2003). What Is an Oil Shock? *Journal of Econometrics*, 113(2):363–398.

Hamilton, J. D. and Jordà, O. (2002). A New Model of the Federal Funds Rate Target. *Journal of Political Economy*, 110(5):1135–1167.

Hansen, P. R. and Lunde, A. (2005). A Realized Variance for the Whole Day Based on Intermittent High-Frequency Data. *Journal of Financial Econometrics*, 3(4):525–554.

Harvey, C. R. (1988). The Real Term Structure and Consumption Growth. *Journal of Financial Economics*, 22:305–333.

Hasbrouck, J. and Seppi, D. J. (2001). Common Factors in Prices, Order Flows, and Liquidity. *Journal of Financial Economics*, 59(3):383–411.

Hautsch, N. (2004). *Modelling Irregularly Spaced Financial Data. Theory and Practice of Dynamic Duration Models*. Berlin: Springer-Verlag.

Hautsch, N. and Hess, D. (2002). The Processing of Non-Anticipated Information in Financial Markets: Analyzing the Impact of Surprises in the Employment Report. *European Finance Review*, 6:133–161.

Hellwig, M. F. (1980). On the Aggregation of Information in Competitive Markets. *Journal of Economic Theory*, 22(3):477–498.

Holden, C. W. and Subrahmanyam, A. (1992). Long-Lived Private Information and Imperfect Competition. *Journal of Finance*, 47(1):247.

Hooker, M. A. (1996). What Happened to the Oil Price-Macroeconomy Relationship? *Journal of Monetary Economics*, 38(2):195–213.

Huang, R. D. and Stoll, H. R. (1994). Market Microstructure and Stock Return Predictions. *Review of Financial Studies*, 7(1):179–213.

IATA (2005). International Air Transport Association World Air Transport Statistics. Special 50th Edition [INTERNET]. Available from: `http://www.iata.org`.

Jain, P. C. (1988). Response of Hourly Stock Prices and Trading Volume to Economic News. *Journal of Business*, 61(2):219–231.

JPMorgan (2008). Emerging Markets Bond Index Monitor February 2008.

Kamstra, M. and Kennedy, P. (1998). Combining Qualitative Forecasts using Logit. *International Journal of Forecasting*, 14:83–93.

Kim, O. and Verrecchia, R. E. (1991a). Market Reaction to Anticipated Announcements. *Journal of Financial Economics*, 30:273–309.

Kim, O. and Verrecchia, R. E. (1991b). Trading Volume and Price Reactions to Public Announcements. *Journal of Accounting Research*, 29:302–321.

Kim, O. and Verrecchia, R. E. (1997). Pre-announcement and Event-period Private Information. *Journal of Accounting and Economics*, 24:395–419.

Kyle, A. S. (1985). Continuous Auctions and Insider Trading. *Econometrica*, 53(6):1315–1336.

Lancaster, T. (1990). *The Econometric Analysis of Transition Data*. Cambridge: Cambridge University Press.

Lee, C. M. C. and Ready, M. J. (1991). Inferring Trade Direction from Intraday Data. *Journal of Finance*, 46(2):733–746.

Li, L. and Engle, R. F. (1998). Macroeconomic Announcements and Volatility of Treasury Futures. Discussion Paper 98-27, Department of Economics, University of California at San Diego.

Madhavan, A. (2000). Market microstructure: A survey. *Journal of Financial Markets*, 3(3):205–258.

Mahmoud, E. (1984). Accuracy in Forecasting: A Survey. *Journal of Forecasting*, 3(2):139–159.

Mandaro, L. (2008). High Oil Prices Put Premium on Hedges; Airlines, Other Major Oil Buyers Keeping a Sharp Eye on the Futures Curve [INTERNET]. *MarketWatch,* 7 January. Available from: `http://www.marketwatch.com`.

Mandelbrot, B. (1963). The Variation of Certain Speculative Prices. *Journal of Business*, 36:394–419.

McQueen, G. and Roley, V. V. (1993). Stock Prices, News, and Business Conditions. *Review of Financial Studies*, 6(3):683–707.

Meitz, M. and Terasvirta, T. (2006). Evaluating Models of Autoregressive Conditional Duration. *Journal of Business and Economic Statistics*, 24:104–124.

Melvin, M. and Yin, X. (2000). Public Information Arrival, Exchange Rate Volatility, and Quote Frequency. *The Economic Journal*, 110(465):644–661.

Milgrom, P. and Stokey, N. (1982). Information, Trade and Common Knowledge. *Journal of Economic Theory*, 26(1):17–27.

Mizrach, B. and Neely, C. J. (2007). The Microstructure of the U.S. Treasury Market. Working Papers 2007–052, Federal Reserve Bank of St. Louis.

Mork, K. A. (1989). Oil and the Macroeconomy When Prices Go Up and Down: An Extension of Hamilton's Results. *Journal of Political Economy*, 97(3):740–744.

Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, 59(2):347–370.

Nofsinger, J. R. and Prucyk, B. (2003). Option Volume and Volatility Response to Scheduled Economic News Releases. *Journal of Futures Markets*, 23(4):315–345.

NYMEX (2006). New York Mercantile Exchange website [INTERNET]. Available from: `http://www.nymex.com`.

NYSE (2006). New York Stock Exchange website [INTERNET]. Available from: `http://www.nyse.com`.

O'Hara, M. (1995). *Market Microstructure Theory*. Cambridge, MA: Blackwell Publishers.

Pacurar, M. (2008). Autoregressive Conditional Duration Models in Finance: A Survey of the Theoretical and Empirical Literature. *Journal of Economic Surveys*, 22(4):711–751.

Papapetrou, E. (2001). Oil Price Shocks, Stock Market, Economic Activity and Employment in Greece. *Energy Economics*, 23(5):511–532.

Patell, J. M. and Wolfson, M. A. (1984). The Intraday Speed of Adjustment of Stock Prices to Earnings and Dividend Announcements. *Journal of Financial Economics*, 13(2):223–252.

Patterson, S. (2006). Dow Hits Six-Year High. *Wall Street Journal*, 27 September.

Raymond, J. E. and Rich, R. W. (1997). Oil and the Macroeconomy: A Markov State-Switching Approach. *Journal of Money, Credit and Banking*, 29(2):193–213.

Rigobon, R. and Sack, B. (2006). Noisy Macroeconomic Announcements, Monetary Policy, and Asset Prices. Working Paper 12420, National Bureau of Economic Research.

Robitaille, P. and Roush, J. (2006). How Do FOMC Actions and U.S. Macroeconomic Data Announcements Move Brazilian Sovereign Yield Spreads and Stock Prices? International Finance Discussion Papers 868, Board of Governors of the Federal Reserve System.

Rotemberg, J. J. and Woodford, M. (1996). Imperfect Competition and the Effects of Energy Price Increases on Economic Activity. *Journal of Money, Credit and Banking*, 28(4):549–577.

Rydberg, T. H. and Shephard, N. (2003). Dynamics of Trade-by-Trade Price Movements: Decomposition and Models. *Journal of Financial Econometrics*, 1(1):2–25.

Sadorsky, P. (1999). Oil Price Shocks and Stock Market Activity. *Energy Economics*, 21(5):449–469.

Simonsen, O. (2006). The Impact of News Releases on Trade Durations in Stocks — Empirical Evidence from Sweden. *Umeå Economic Studies*, 688.

Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica*, 48:1–48.

Smallen, D. (2006). 2005 Total Airline System Passenger Traffic Up 4.6 Percent from 2004. Technical Report BTS 20-06, U.S. Department of Transportation, Bureau of Transportation Statistics. Available from `http://www.bts.gov`.

Smith Barney (2006). Citibank Smith Barney website [INTERNET]. Available from: `https://www.smithbarney.com`.

Stock, J. H. and Watson, M. W. (1989). New Indexes of Coincident and Leading Economic Indicators. In Blanchard, O. and Fischer, S., editors, *NBER Macroeconomics Annual*, volume 4. The MIT Press.

Stoll, H. R. (2003). Market Microstructure. In Constantinides, G., Harris, M., and Stulz, R., editors, *Handbook of the Economics of Finance*, volume 1, chapter 9, pages 553–604. Amsterdam: Elsevier North Holland.

TAQ 3 User's Guide (2006). TAQ 3 User's Guide. Version 1.0.5. New York Stock Exchange, Inc.

Teräsvirta, T. and Anderson, H. M. (1992). Characterizing Nonlinearities in Business Cycles Using Smooth Transition Autoregressive Models. *Journal of Applied Econometrics*, 7:119–136. Reprinted in Nonlinear Dynamics, Chaos and Econometrics, edited by M.H. Pesaran and S.Potter (Wiley) 1993.

Timmermann, A. (2006). Forecast Combinations. In Elliott, G., Granger, C., and Timmermann, A., editors, *Handbook of Economic Forecasting, Volume 1*. Amsterdam: North-Holland.

Trade Association for the Emerging Markets (2008). Fourth Quarter 2007 Debt Trading Volume Survey.

Twin, A. (2006). Oil, Mideast Pummel Stocks. *CNN Money,* 13 July. Available from: `http://money.cnn.com`.

Ulph, C. J. (1999). *Modelling Irregularly Spaced Transactions in Financial Markets*. PhD thesis, Department of Economics and Business Statistics, Faculty of Business and Economics, Monash University.

UN-DESA (2005). United Nations Department of Economic and Social Affairs, World Economic Situation and Prospects 2005.

U.S. Department of Energy (2006). U.S. Department of Energy [INTERNET]. Available from: `http://www.energy.gov`.

Veredas, D. (2006). Macroeconomic Surprises and Short-term Behaviour in Bond Futures. *Empirical Economics*, 30:843–866.

Veredas, D., Rodriguez-Poo, J. M., and Espasa, A. (2002). On the (Intradaily) Seasonality and Dynamics of a Financial Point Process: A Semiparametric Approach. CORE Discussion Paper 2002/23, Université Catholique de Louvain, Louvain-La-Neuve.

Vergote, O. (2005). How to Match Trades and Quotes of NYSE Stocks? Center for Economic Studies Discussion Paper DPS 05.10., K.U. Leuven.

Wenning, T. (2006). Airline Stocks Are Flying High. *Motley Fool,* 21 September.

West, K. D. (2001). Tests for Forecasts Encompassing When Forecasts Depend on Estimated Regression Parameters. *Journal of Business and Economic Statistics*, 19:29–33.

West, K. D. (2006). Forecasting Evaluation. In Elliott, G., Granger, C., and Timmermann, A., editors, *Handbook of Economic Forecasting, Volume 1.* Amsterdam: North-Holland.

West, K. D. and McCracken, M. W. (1998). Regression-Based Tests of Predictive Ability. *International Economic Review*, 39(4):817–840.

White, H. (1982). Maximum Likelihood Estimation of Misspecified Models. *Econometrica*, 50(1):1–25.

Wongswan, J. (2006). Transmission of Information across International Equity Markets. *Review of Financial Studies*, 19(4):1157–1189.

Zhang, M. Y., Russell, J. R., and Tsay, R. S. (2001). A Nonlinear Autoregressive Conditional Duration Model with Applications to Financial Transaction Data. *Journal of Econometrics*, 104(1):179–207.